Price-Based Return Comovement

T. Clifton Green and Byoung-Hyoun Hwang*

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Abstract

Similarly priced stocks move together. Stocks that undergo splits experience an increase in comovement with lower priced stocks and a decrease in their comovement with higher priced stocks. Price-based comovement is not explained by economic fundamentals, firm size, or changes in liquidity or information diffusion. The shift in comovement following splits is greater for large stocks, high priced stocks, and when investor sentiment is high. In the full cross-section, price-based portfolios explain variation in stock-level returns after controlling for movements in the market and industry portfolios as well as portfolios based on size, book-to-market, and return momentum. The results suggest that investors categorize stocks based on price.

*Both authors are from Goizueta Business School, Emory University, 1300 Clifton Rd., Atlanta, GA 30322. Email: Clifton_Green@bus.emory.edu and Byoung-Hyoun_Hwang@bus.emory.edu.

The tendency of security prices to move together is a fundamental component of asset pricing theory and influences practical asset allocation strategies. The traditional view of comovement holds that stock prices move together in response to market-wide information. However, a number of authors contend that observed stock return comovement appears excessive relative to fundamentals. For example, Shiller (1989) argues that the comovement between U.K. and U.S. stock prices is too large to be fully explained by comovement in dividends.[1]

Recent research documents several specific sources of stock return comovement that appear unrelated to fundamentals. For example, Barberis, Shleifer, and Wurgler (2005) find that stocks added to the S&P 500 index begin to covary more with other members of the index, and Greenwood (2007) finds similar evidence for the Nikkei 225. Also, Pirinsky and Wang (2006) find that stocks in the same geographical area move together in ways not fully explained by fundamentals. In other work, Kumar and Lee (2006) document that correlated trading among retail investors leads to excess stock return comovement, and Pirinsky and Wang (2004) provide similar evidence for institutional investors.

These papers support a role for category investing in the price formation process. Barberis and Shleifer (2003) model an environment where investors simplify portfolio decisions by grouping assets into styles or categories and then allocate funds at the category level rather than across individual securities. If style investors respond in similar ways to changes in market sentiment (e.g. Baker and Wurgler, 2006), then as they move

[1] Other work on excess comovement includes Lee, Shleifer, and Thaler (1991), Pindyck and Rotemberg (1993) and Froot and Dabora (1999).

funds from one category to another their coordinated demand is likely to induce common factors in the returns of otherwise unrelated assets.

In this article, we uncover a new source of return comovement related to stock price. It's reasonable to think investors might categorize stocks based on price. In many economic settings price can facilitate comparisons across assets. For example, when evaluating new cars in terms of performance and amenities, it is reasonable to conclude that a Toyota sedan is more similar to a Honda than a BMW from observing prices. This type of comparison is useful and commonplace in economic decision making and it may be natural for investors to group stocks based on price. Moreover, stock price also tends to be cross-sectionally related to market capitalization, and it's possible some investors may consider price to be a readily available a proxy for firm size.

In practice a firm's number of shares outstanding can be changed arbitrarily through stock splits, which makes cross-sectional comparisons of price per share relatively meaningless. Despite the disconnect between nominal share prices and underlying value, Benartzi, Michaely, Thaler, and Weld (2006) provide evidence that stock prices are important to investors. They document that the nominal prices of common stocks have remained constant at around $30 per share since the Great Depression as a result of firms proactively splitting their stocks, which the researchers find difficult to fully rationalize.

If investors categorize stocks based on price, it may explain why managers split their stocks rather than letting their prices deviate significantly from their peers. Although researchers have sought explanations for splits that involve transaction costs or managers' private information (e.g. Schultz, 2000, and McNichols and Dravid, 1990), the literature generally concludes that stock splits are geared towards returning stock prices to a "normal range" (e.g. Lakonishok and Lev, 1987, and Dyl and Elliott, 2006). The fact that companies that shun splits, most famously Warren Buffett's Berkshire Hathaway and more recently Google, are seen as maverick provides anecdotal evidence that markets view nominal prices as important.[2]

Stock splits provide a natural experiment for testing whether investors categorize stocks based on price. Splits induce large changes in nominal prices with no accompanying change in firms' fundamentals. As such, they provide a clean test of category-based investing with few confounding influences. Our specific approach is to look for shifts in split stocks' comovement with price-indexed portfolios before and after the split.

Our evidence supports the view that investors categorize stocks based on price. We find that stocks that undergo splits experience an increase in comovement with lower priced stocks and a decrease in comovement with higher priced stocks. The results are not attributable to changes in fundamentals such as systematic risk, changes in firm characteristics such as size or liquidity, or changes in the speed of information diffusion. The findings are consistent within subsamples and withstand a number of robustness checks including matching firm controls.

We conjecture that small investors are more likely to categorize stocks based on price due to greater difficulty in obtaining market information and higher susceptibility to behavioral biases. Kumar and Lee (2006) show that individual investors favor small, low-

[2] Consider also the statement from Palm, Inc. explaining a recent stock split. "The split … will help the company align its capital structure to that of companies with comparable revenue." Although a split has no economic effect on capital structure, the description gives the impression that nominal prices are relevant to investors. http://www.palm.com/us/company/pr/2006/021306b.html.

priced stocks and tend to trade in conjunction. If the shift in comovement following splits is driven by small investors, we would expect greater shifts for stocks that become more attractive to individual investors after the split. The evidence backs up this conjecture. We find the change in comovement following splits is greater for large, high-priced stocks and when investor sentiment is high, which supports the hypothesis that firms split to become more attractive to small investors.

Our final set of tests investigates whether price-based categorization influences stock returns in the full cross section of stocks. We construct price-based indexes using NYSE quintile breakpoints from the previous year and examine whether these portfolios explain returns after controlling for common return factors. Regressing returns on non-overlapping portfolios based on price, firm size, book-to-market, industry, and return momentum reveals that price categorization has a pervasive effect on stock returns. The loadings on the price index are similar in magnitude to the loadings on the other factors.

Taken together, our findings suggest nominal prices are relevant to investors when constructing and rebalancing their portfolios. Price-based categorization of stocks has a material effect on return dynamics, and provides additional support to sentiment-based explanations for return comovement. Our results also add to the literature on stock splits by offering a justification for “trading range” motivations for splits.

The rest of the paper is organized as follows: Section 1 describes the sample, Section 2 presents evidence of shifts in price-based return comovement around stock splits, Section 3 extends the sample to all stocks and provides evidence of price-based return comovement in the full cross section, and Section 4 concludes.

1. Data and Descriptive Statistics

The data is from CRSP and includes all ordinary common shares listed on NYSE, AMEX and NASDAQ between 1926 and 2004. For the sample of stock splits, we consider all stocks for which the *Factor to Adjust Prices* variable in CRSP indicates that a stock split occurred. We focus on 2-for-1 stock splits, which account for roughly 80% of all splits with a split factor of greater than or equal to 2-for-1. We exclude stocks with post-split prices less than $5 and require stocks to have return data in CRSP over the 12-month period ending one month before the split and over the 12-month period beginning one month after the split. The final split sample contains 5,424 events.

Table 1 reports descriptive statistics for the distribution of stock prices. Each month, we take the cross-sectional mean and decile breakpoints of stock prices for all NYSE, AMEX and NASDAQ stocks with a price greater than $5. The time-series means of those statistics are presented in Panel A of the table. Given the dramatic growth in the stock market over the last 80 years, nominal stock prices are remarkably stable over time. The apparent drop in prices beginning in the 1970s is mainly due to the inclusion of NASDAQ stocks in the sample.[3] Panel B reports the distribution of the pre-split prices for the sample of firms that split. Not surprisingly, pre-split prices tend to be relatively high. The median pre-split price is $51.44, which corresponds to roughly the 85th percentile of stock prices in the full cross-section. The 10th percentile pre-split price is $27.00, which places it just above the 60th percentile of stock prices in the cross-section.

In a recent paper, Benartzi, Michaely, Thaler, and Weld (2006) also document stability in stock prices over time, and suggest that firms' splitting behavior presents a

[3] The prices of NYSE stocks continue to be very similar to the earlier period. The median prices for NYSE stocks during the three subperiods are 28.11, 22.86, and 25.30.

puzzle. Next, we investigate the extent to which investors categorize stocks based on price, which could provide a partial explanation for why firms split.

2. Price-Based Comovement: Evidence from Stock Splits

We begin our analysis by examining priced-based return comovement around stock splits. Let P_{pre} and P_{post} be the pre- and post-split stock prices measured one day before the split. For each stock split, at each point in time we group stocks into low and high price portfolios according to the following classification:

$$LowPrc \in \left[P_{post} - \frac{\left(P_{pre} - P_{post}\right)}{2}, P_{post} + \frac{\left(P_{pre} - P_{post}\right)}{2} \right], \text{ and}$$

$$HighPrc \in \left[P_{pre} - \frac{\left(P_{pre} - P_{post}\right)}{2}, P_{pre} + \frac{\left(P_{pre} - P_{post}\right)}{2} \right].$$

Since we focus on 2-for-1 stock splits this can be written more succinctly as:

$$LowPrc \in \left[\frac{1}{4} P_{pre}, +\frac{3}{4} P_{pre} \right], \text{ and } HighPrc \in \left[\frac{3}{4} P_{pre}, +\frac{5}{4} P_{pre} \right].$$

For example, if a stock splits from \$60 to \$30, the high price category includes stocks with prices between \$45 and \$75, and the low price category includes stocks with prices between \$15 and \$45. We calculate value-weighted portfolio returns for the low and high price portfolios on a daily and weekly frequency.[4]

2.1. Univariate and Bivariate Tests

If investors categorize stocks based on price, after the split we would expect stocks to covary more with stocks in the low price category. To test this hypothesis, for

[4] This methodology produces high and low price indexes for each split. As a robustness check, we also fix price index quintile portfolios each year in December using NYSE prices and examine splits where prices switch quintiles. Using this fixed price methodology produces similar results.

each stock split we estimate the following univariate regression separately before and after the split:

$$R_{i,t} = \alpha_i + \beta_{LowPrc,i} R_{LowPrc,i,t} + \varepsilon_{i,t}\ , \tag{1}$$

where $R_{i,t}$ is the return of firm *i* at time *t* and $R_{LowPrc,i,t}$ is firm *i*'s respective low price index at time *t*. To avoid spurious effects, we remove the contribution of the split stock from the right-hand-side variable where appropriate. We estimate the regression for daily and weekly returns. For both data frequencies, the pre-event regression is run over the 12-month period ending one month before the split implementation, and the post-event regression is run over the 12-month period starting one month after the split implementation. Standard errors are clustered by month when calculating t-statistics to account for cross-sectional correlation across stocks.

Table 2 reports the cross-sectional mean of the change in the slope coefficient, $\overline{\Delta\beta_{LowPrc}}$, and the cross-sectional mean of the change in adjusted R-squared, $\overline{\Delta\overline{R}^2}$. The results show an increase in both the low price index coefficient and the adjusted R-squared. In the full sample, the mean increase in the price index coefficient is 0.219 for daily returns and 0.191 for weekly returns, and the changes are statistically significant within each subperiod. The adjusted R-squared increases by around 3% for both daily and weekly returns. In comparison, Barberis et al. (1998) find that after a stock is added to the S&P 500, its daily (weekly) beta on the S&P 500 index increases by 0.151 (0.110) on average. It is also interesting to note that, for both daily and weekly data, the change in the coefficient has been increasing over the three subperiods. This suggests that the importance of price categories has not diminished over the course of our sample.

One concern is that the results may be driven by faster information diffusion following the split. If splits increase liquidity, then stocks may respond more quickly to market-wide information and result in greater contemporaneous comovement and higher betas. The fact that we observe similar shifts in comovement using both daily and weekly data mitigates this concern, but we return to this issue with a specific test in a later section.

Another relevant concern is changes in systematic risk around the split. Ohlson and Penman (1985) and others document that stocks experience increased volatility following splits. Thus, we also use a bivariate approach to control for changes in systematic risk. If investors categorize stocks based on price, following the split the stock will have a higher loading on the low price category index and a lower loading on the high price category index. The regression specification is:

$$R_{i,t} = \alpha_i + \beta_{LowPrc,i} R_{LowPrc,i,t} + \beta_{HighPrc,i} R_{HighPrc,i,t} + \varepsilon_{i,t}. \qquad (2)$$

Table 3 reports the cross-sectional mean of the changes in the slope coefficients, $\overline{\Delta\beta_{LowPrc}}$ and $\overline{\Delta\beta_{HighPrc}}$. The bivariate results confirm the findings from the univariate regressions. For both daily and weekly data, a split is associated with an economically and statistically significant increase in the beta on the low price index and an economically and statistically significant decrease in the beta on the high price index. In the full sample, the average low price index coefficient increases by 0.343 for daily returns and by 0.355 for weekly returns whereas the average high price index coefficient decreases by -0.131 for daily returns and by -0.171 for weekly returns. As with the univariate case, the results are the strongest in the most recent subperiod, 1991-2004.

Peterson (2007) highlights the difficulty of controlling for time series dependency in panel data. As a robustness check, we also use a Fama-Macbeth type approach to control for cross-sectional correlation in the data. Specifically, for each split we record the changes in the slope coefficients $\Delta\beta_{LowPrc,i}$ and $\Delta\beta_{HighPrc,i}$ from the univariate and bivariate regressions (1) and (2). We then take the cross-sectional mean of the changes in the slope coefficients for all splits occurring within a particular month. We do this for all months in which there is at least one stock split and then take the time-series mean of the cross-sectional means of the changes in the slope coefficients, $\overline{\overline{\Delta\beta_{LowPrc}}}$ and $\overline{\overline{\Delta\beta_{HighPrc}}}$. To control for potential time-series correlation, we adjust standard errors using Newey-West with 36 lags.

Table 3 reports the results. The results generally confirm the findings in Table 2. In the univariate case, at both daily and weekly frequencies, the beta on the low price index and the adjusted R-squared increase significantly. In the bivariate case, the results continue to be supportive of price-based comovement at all frequencies, although the decrease in the coefficient on the high price index is weaker in the middle subperiod.

2.2 Matching Firms

To further alleviate concerns that the shift in comovement reflects a change in fundamentals, we also calculate excess changes in coefficients by subtracting corresponding estimates for matching firms similar to Barberis et al. (2005). For each firm conducting a stock split, we select a control firm, drawn from the same industry as the event stock and in the same size decile both at the time of the split and 12 months prior to the split, but which does not conduct a split in the previous year. Since the matching stock matches the event stock on industry and recent growth in market capitalization, it is arguably as good a candidate for a stock split as the event stock itself. If the matching stock's beta on the low price category index (high price category index) does not increase (decrease), it strengthens our argument that the results in Table 2 are unrelated to fundamentals.

For all splits and matching stocks, we run the univariate and bivariate regressions (1) and (2). In this part of the analysis, we require not only the split firms to have complete returns data over the event horizon but also suitable matching firms to have complete returns data over the same horizon. This reduces our sample to 4,929 splits.

For the univariate regression, we examine the mean change in slope and the mean change in fit for stocks conducting a split minus the corresponding quantities for matching stocks, $\overline{\Delta\Delta\beta_{LowPrc}}$ and $\overline{\Delta\Delta\bar{R}^2}$. For the bivariate regression, we examine the mean change in the slopes for stocks conducting a split minus the corresponding quantities for matching stocks, $\overline{\Delta\Delta\beta_{LowPrc}}$ and $\overline{\Delta\Delta\beta_{HighPrc}}$. Again, standard errors are clustered by month.

Table 4 presents the results. The changes in the coefficients and adjusted R-squared remain strongly significant in the univariate case after subtracting off the corresponding changes for matching stocks. In the bivariate case, the results also continue to be strong and remain statistically significant in the full sample and in two of the three subperiods.

Figure 1 extends the exercise in Table 4 to rolling windows around the split and graphically shows the evolution in price index coefficients. The figures plot the mean average slope coefficients from the bivariate regression (2) for returns of stocks conducting a split and their respective matching firms on returns of the stocks' high price category index and the stocks' low price category index. We also plot the mean coefficients from regressions of the split stock return on the value-weighted CRSP market return. The sample includes all firms that have complete returns data over the entire event horizon examined in each figure (-12 to +24 months), and for which suitable matching firms exist that have complete data over the same horizon.

Figure 1 confirms the results in Table 4. The matching firms exhibit much smaller shifts in betas than do the split firms. Consistent with Brennan and Copeland (1988), we find that market betas increase around the split. However, as we can see in Figure 1, the change in the coefficient on the low price index is much larger than the change in the market beta. Furthermore, we also find that the coefficient on the high price index decreases after the split. This suggests that our finding is distinct from the change in market beta documented by Brennan and Copeland (1988).

The relative magnitudes of the price-index betas also deserve comment. Given the relatively high pre-split price (recall that the median pre-split price corresponds to roughly the 85th percentile of stock prices in the full cross-section), the low price category often consists of many more stocks than the high price category and likely mirrors the market return more closely than the high price index. As a result, in absolute terms firms generally covary more with the low price index than the high price index. For our purposes we are more interested in changes in comovement. However, as a robustness check we examine splits with a relatively low pre-split price, e.g. firms splitting from $20 to $10, where the high price index contains more stocks than the low price index. For this restricted sample, we find split firms covary more in absolute terms with the high price index than with the low price index before the split, and that this relation reverses after the split.

2.3. Controlling for Changes in Liquidity and Speed of Information Dissemination

One motivation for stock splits is to improve the liquidity of the stock by enlarging the firm's investor base. If splits improve liquidity, then perhaps this could have an effect on the stock's return characteristics and influence our comovement results. Although no specific study shows that returns for stocks with similar liquidity are correlated, Pastor and Stambaugh (2003) and Acharya and Pedersen (2003) show that changes in liquidity can have implications for expected returns, and Chordia, Roll, and Subrahmanyam (2000) and Hasbrouck and Seppi (2001) find evidence that stock liquidity tends to move together in the cross-section.

The empirical evidence regarding the effects of splits on liquidity is mixed. Lamoureux and Poon (1987) find that the number of shareholders increases after a split and more recently Kadapakkam, Krishnamurhty, and Tse (2006) find an increased intensity of small investor buying. However, Copeland (1979) and Lakonishok and Lev (1987) find that splits have no long-term impact on volume, and Schultz (2000) documents that trading costs tend to increase following splits.

In our sample, we find turnover falls in the year following the split and no significant change in dollar volume. Specifically, for each split stock we calculate the change in average daily turnover (volume scaled by shares outstanding) and the percentage change in daily volume in the year before and after the split and subtract the same measure for a matching firm. Matching firms are chosen as described in Section 2.2 with the added stipulation that the firms are chosen from the same stock exchange.

We find average daily turnover for NYSE (Nasdaq) stocks before the split is 0.27% (0.67%), and the average difference in turnover around the split minus the same number for the matching firm is -0.034%, with a t-stat of 2.55. Average dollar volume for NYSE (Nasdaq) stocks before the split is $11.3 ($13.8) billion, and the average percentage change in dollar volume around the split minus the same number for the matching firm is 9.4% with a t-stat of 0.86. Thus, our evidence suggests splits have at most a marginal effect on liquidity over the annual horizon we study comovement.

A related concern is whether the information dissemination changes following splits. Splits typically follow a period of outperformance which could lead to greater visibility and more efficient pricing. As a result, firms may respond more quickly to market-wide information following stock splits, in which case loadings on current market returns would increase and loadings on lagged returns may decrease. We follow Dimson (1979), and Barberis et al. (2005) and attempt to identify the effect of information diffusion by including leading and lagged low price category index returns and high price category index returns in the univariate and bivariate regressions. Specifically, for daily frequency data, we estimate the regressions

$$R_{i,t} = \alpha_i + \sum_{s=-5}^{5} \beta_{LowPrc,i}^{(s)} R_{LowPrc,i,t+s} + \varepsilon_{i,t}, \quad (3)$$

and

$$R_{i,t} = \alpha_i + \sum_{s=-5}^{5} \beta_{LowPrc,i}^{(s)} R_{LowPrc,i,t+s} + \sum_{s=-5}^{5} \beta_{HighPrc,i}^{(s)} R_{HighPrc,i,t+s} + \varepsilon_{i,t} \quad (4)$$

both before and after the stock split, thereby including five leads and lags. The changes in the quantities

$$\sum_{s=-5}^{5} \beta^{(s)}_{LowPrc,i}\ ,\ \sum_{s=-5}^{5} \beta^{(s)}_{LowPrc,i}\ \text{ and } \sum_{s=-5}^{5} \beta^{(s)}_{HighPrc,i} \tag{5}$$

across event dates can be interpreted as the beta shifts that would occur in a world without any delay in the incorporation of information. Standard errors are clustered by month.

Table 5 reports the average changes in the quantities in (5) across split dates. We can see that the numbers in Table 5 are very similar in magnitude to those in Table 2. For both the univariate and bivariate case, information diffusion accounts for a relatively small portion of the economic magnitude. The residual change, attributable to category effects only, remains strongly significant. In comparison, in Barberis et al. (1998) information diffusion accounts for roughly two-thirds of the economic magnitude of their bivariate results. It is interesting to note that the slight drop in economic magnitude in the full sample is mainly due to a drop in economic magnitude in the first subperiod, 1926-1970. This suggests that while information diffusion might have played a role in explaining the shift in betas around stock splits in the earlier period, this is much less so the case in the more recent parts of our sample.

In sum, we find that after conducting a split the stock begins to covary more with lower priced stocks and less with higher priced stocks. Price-based comovement is neither explained by firm characteristics nor by information diffusion. The results suggest that investors categorize stocks based on price.

2.3. Determinants of Comovement following Splits

In this section we examine determinants of the shift in comovement following splits in hopes of shedding light on which types of investors categorize stocks based on price. We conjecture that small investors may be more likely to exhibit this type of behavior. In general small investors face greater difficulty in obtaining market information than professional investors. Stock price and market capitalization tend to be correlated in the cross-section, and to the extent that data on capitalization may be harder to obtain than price, individual investors may use price as a naïve proxy for size. Research also suggests that individual investors may be more susceptible to behavioral biases. For example, Grinblatt and Keloharju (2000, 2001) find evidence that small investors are more subject to cultural and language biases as well as the disposition effect (detrimental tendency to sell winners and hold losers).

A number of authors document that splits make stocks more attractive to small investors.[5] Our specific hypothesis is that a stock split will lead to a greater shift in comovement if the stock becomes relatively more attractive to retail investors after the split. Kumar and Lee (2006) find that retail investors tend to hold small, low priced stocks, and we investigate shifts in comovement related to these characteristics. We also hypothesize that the change in beta coefficients will be greater in times of high investor sentiment. High investor sentiment stimulates noise trading and could lead to greater category-based comovement. Finally, we expect the shift in comovement to be smaller for stocks with high institutional ownership.

In order to examine determinants of the shift in return comovement following stock splits, we construct a measure of the cumulative change in the two beta coefficients: for each split, we estimate the bivariate regression (2) separately for the period before the split and the period after the split and record the changes in the slope

[5] For example, Schultz (2000) finds evidence of more small traders following splits. Easley, O'Hara, and Saar (2001) find greater uninformed trading following splits, and Dhar, Goetzmann, Shepherd, Zhu (2004) find increased retail trading following splits.

coefficients, $\Delta\beta_{LowPrc}$ and $\Delta\beta_{HighPrc}$. The measure of cumulative change in the two betas is defined as $\Delta\beta_{cumulative} = \left(\Delta\beta_{LowPrc} - \Delta\beta_{HighPrc}\right)$ which we calculate separately for daily and weekly return frequencies.

We use $\Delta\beta_{cumulative}$ as our measure of the cumulative change in comovement following the split, and regress this measure on a number of split characteristics. We include firm size as the log of the market capitalization in $Millions at the end of the month prior to the split. Market price is measured the day prior to the split. Our measure of investor sentiment is the *sf*1 sentiment factor of Baker and Wurgler (2006), constructed as the first principal component of the closed-end fund discount, the gross equity issuance divided by the gross equity plus gross long-term debt issuance, and the detrended log turnover.[6] We calculate institutional holdings as the proportion of shares held by institutions during the quarter before the split, $Inst.Hold_{i,t}$. Since the institutional holdings variable restricts the sample substantially, we regress the cumulative change in beta separately on the institutional holdings variable. Standard errors are clustered by month, and the results are presented in Table 6.

The findings are generally consistent with our hypotheses. The coefficient on market sentiment is positive and statistically significant, suggesting that a change in the investor base towards retail investors is more likely to occur in times of high investor sentiment. The magnitude of the coefficient is 0.1 for daily and 0.2 for weekly. This implies that a one standard deviation increase in the market sentiment proxy, on average, leads to an increase in the cumulative change in the betas of 0.1 and 0.2 respectively.

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[6] We utilize their first sentiment factor, *sf*1, rather than their second sentiment factor, *sf*2, because it has a longer time series. When we use *sf*2, the coefficient on *sf*2 is even more significant than the reported coefficient on *sf*1. The data is from Jeff Wurgler's website http://pages.stern.nyu.edu/~jwurgler.

We also find the shift in comovement increases significantly in firm size, which suggests large firms may try to appear small by splitting their stocks.[7] We find modest evidence that the shift in comovement increases for firms with high pre-split prices, but this appears mainly driven by size. The coefficient on institutional ownership has the hypothesized sign but is statistically insignificant.

Together, the results show that shifts in comovement following stock splits are greater for large stocks and during times of high market sentiment. The results are consistent with the interpretation that stocks conducting a split are more likely to be bought by retail investors (who did not previously own the stock) when the stock is not already widely held by retail investors. This has policy implications for firms conducting stock splits to become more attractive to retail investors.

3. Price-Based Return Comovement: All Stocks

We now shift our analysis away from stock splits and examine whether price-based categorization affects the comovement in the full cross-section of stocks. Moving away from stock splits requires a new methodology to measure price categories. We define price categories from January to December of year t as the quintile breakpoints for the stock price of NYSE stocks at the end of December of year t-1. While this definition of price categories is admittedly arbitrary, the results are robust to alternative definitions of price categories. We exclude stocks with stock prices below $5.

We then run the following stock-level time-series regression:

$$R_{i,t} = \alpha_i + \beta_{PRC,i} R_{PRC,i,t} + \beta_{Mkt,i} R_{Mkt,t} + \varepsilon_{i,t} \quad (6)$$

[7] This theory is advanced in recent work by Baker, Greenwood, and Wurgler (2007).

where $R_{i,t}$ is the stock return of firm *i* at time *t*, and $R_{PRC,i,t}$ is the price category index return of firm *i* at time *t*.

The price category index return is constructed as follows: Each day for daily data and each week for weekly data, we assign NYSE, AMEX and NASDAQ stocks to five portfolios based on their price categories. To ensure that our price category stock return index is not simply capturing some characteristic other than the stock price, in calculating price category index returns we exclude stocks that are in the same industry (using the Fama and French 12 industry classification) and/or in the same size quintiles[8]. We control for industry because certain price ranges might be more common in certain industries. We control for firm size since stock price tends to positively correlated to market capitalization. Size quintiles are formed based on the quintile breakpoints for the market capitalization of NYSE stocks at the end of December of the previous year. An example clarifies how we exclude same-industry-size stocks: If firm *i* was in the bottom price and bottom size quintile and in the Consumer Durables industry, its respective price category index return would be constructed using all NYSE, AMEX and NASDAQ stocks that are in the bottom price quintile but are not in the bottom size quintile and/or in the Consumer Durables industry. We value weight all portfolios. $R_{Mkt,t}$ is the value-weighted CRSP market return at time *t*. The market return is included in the regression to control for overall market-wide comovement.

To more thoroughly control for size, we modify equation (6) by introducing a value-weighted size index, that is,

$$R_{i,t} = \alpha_i + \beta_{PRC,i} R_{PRC,i,t} + \beta_{SIZE,i} R_{SIZE,i,t} + \beta_{Mkt,i} R_{Mkt,t} + \varepsilon_{i,t}, \quad (7)$$

[8] The results continue to stand if we also exclude stocks that are in adjacent size quintiles.

where $R_{SIZE,i,t}$ is the value-weighted size index return of firm i at time t. The size index consists of all stocks that are in the same size quintile but not in the same industry and/or the same price quintile as stock i.

Similarly, in order to more thoroughly control for industry, we modify equation (6) by introducing a value-weighted industry index of the stock's corresponding industry group:

$$R_{i,t} = \alpha_i + \beta_{PRC,i} R_{PRC,i,t} + \beta_{IND,i} R_{IND,i,t} + \beta_{Mkt,i} R_{Mkt,t} + \varepsilon_{i,t}\,, \tag{8}$$

where $R_{IND,i,t}$ is the value-weighted industry index return of firm *i* at time *t*. The industry index consists of all stocks that are in the same industry but not in the same size and/or the same price quintile as stock i.

Finally, we run a regression in which we include both the value-weighted size index and the value-weighted industry index:

$$R_{i,t} = \alpha_i + \beta_{PRC,i} R_{PRC,i,t} + \beta_{Size,i} R_{Size,i,t} + \beta_{IND,i} R_{IND,i,t} + \beta_{Mkt,i} R_{Mkt,t} + \varepsilon_{i,t}\,. \tag{9}$$

In our last regression, we use an alternative way to control for firm characteristics. We utilize benchmark portfolios as in Daniel, Grinblatt, Titman, and Wermers (1997) and Wermers (2004).[9] Stocks are assigned ton one of 125 benchmark portfolios based on size, book-to-market, and return momentum. We create weekly and daily value-weighted benchmark portfolio returns similar to above and run the following regression:

$$R_{i,t} = \alpha_i + \beta_{PRC,i} R_{PRC,i,t} + \beta_{DGTW,i} R_{DGTW,i,t} + \beta_{Mkt,i} R_{Mkt,t} + \varepsilon_{i,t}\,, \tag{10}$$

where $R_{DGTW,i,t}$ is firm *i*'s respective characteristics-based benchmark return at time t.

[9] The data is obtained from Russ Wermers' website (http://www.smith.umd.edu/faculty/rwermers/).

We first estimate equations (6) through (10) as stock-level time-series regressions and take the cross-sectional mean of the coefficients. We require at least one year of observations for both daily and weekly data. Given that the characteristics-based benchmark returns start only in 1974, to facilitate comparisons, we restrict ourselves to the time period starting in 1974 and ending in 2005. Extending our time period for equations (6) to (9) strengthens the results. Overall, we have 10,750 stocks. The standard errors are adjusted for cross-correlation and heteroskedasticity using GMM. To keep our analysis computationally feasible, we do the GMM only for weekly data and then use the weekly adjustment factor $\left(\dfrac{stderr_{no\ adjustement}}{stderr_{GMM}}\right)$ to adjust the standard errors for daily data. This is quite conservative, as we would expect more cross-correlation for weekly data than for daily data due to slow information diffusion.

As can be seen in Table 7, the beta on the price category index is positive and highly significant in all cases. For daily returns, the average betas range from 0.149 to 0.379. For weekly returns, the average betas range from 0.209 to 0.460. In comparison, when Pirinsky and Wang (2006) examine whether stocks in the same geographical area move together and run a time-series regression of monthly stocks returns on a local index, industry index, and market index, the coefficient on their local index is around 0.5.[10] The regression that most closely resembles the time-series regression of Pirinsky and Wang (2006) is regression (III) for weekly data where we run a time-series regression of weekly stock returns on a price index, industry index, and market index.

[10] They do not report the coefficient for their full sample. The coefficient in the first subperiod is 0.545, the coefficient in the second subperiod is 0.532, and the coefficient in the third subperiod is 0.459.

The coefficient on the price index is equal to 0.460. The magnitude of price comovement, thus, is comparable to the magnitude of local comovement in Pirinsky and Wang (2006).

As a robustness check, we also do a Fama-MacBeth type analysis. Each year, we run stock-level time-series regressions. We then take the cross-sectional mean of all coefficients of the betas. We do this each year and take the time-series mean of those cross-sectional means. The results are presented in Table 8.

Again, the beta on the price category index is positive and significant for all regressions and all data frequencies. For daily returns, the average betas range from 0.070 to 0.281. For weekly returns, the average betas range from 0.075 to 0.323. Taken together, our findings suggest that price-based comovement is not limited to stock splits but is more broadly evident in the full cross-section of stocks.

4. Conclusions

One difficulty with detecting sentiment-based comovement driven by investment styles is that stock categories are often economically related or face other common frictions. For example, Pirinsky and Wang (2006) find evidence that stocks in the same geographical area move together in ways not fully explained by fundamentals. Yet this interpretation hinges on their ability to fully control for the fact that industries cluster geographically. In other work, Barberis, Shleifer, and Wurgler (2005) find that stocks added to (deleted from) the S&P 500 index begin to covary more (less) with other members of the index. Their findings are consistent with category investing based on the S&P 500, but the large sums invested in S&P 500 index funds alone may drive this result which narrows its applicability to the broader market.

In this study, we present evidence of a new investment category related to nominal stock price. Stock splits induce large changes in nominal prices with no accompanying change in firms' fundamentals. As such, they provide a clean test of category-based investing with few confounding influences. Our analysis involves looking for shifts in split stocks' comovement with price-indexed portfolios before and after the split.

Our evidence supports the view that investors categorize stocks based on price. We find that stocks that undergo splits experience an increase in comovement with lower priced stocks and a decrease in comovement with higher priced stocks. The shift is not attributable to changes in fundamentals, firm characteristics such as size, or changes in the speed of information diffusion. We find the shift in comovement following splits is greater for large stocks, high priced stocks, and when investor sentiment is high, which suggests that small investors may be more likely to categorize stocks based on price.

Our findings provide a justification for "trading range" explanations for stock splits. If investors group stocks based on price, a firm with a stock price significantly different from its peers has the incentive to split rather than risk facing smaller pool of investors. Building on the results here, Baker, Greenwood, and Wurgler (2007) argue that managers strategically respond to investors' preferences regarding price, finding that splits are more likely when investors place higher valuations on low-price firms.

Price-based comovement is also evident in the full cross-section of stocks. Price-based portfolios explain variation in stock-level returns after controlling for movements in the market and industry portfolios as well as portfolios based on size, book-to-market, and return momentum. Taken together, our results emphasize the importance of investor sentiment for valuation, and suggest that nominal prices are relevant to investors when constructing and rebalancing their portfolios.

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Table 1
Descriptive Statistics
Data is from the Center for Research in Security Prices (CRSP), and includes all ordinary common shares with a stock price greater than $5. At the end of each month, we take the cross-sectional mean and decile breakpoints of the stock prices of all NYSE, AMEX and NASDAQ stocks. In Panel A, we report the time-series mean of the cross-sectional means and decile breakpoints. Panel B presents summary statistics on the pre-split prices of firms conducting a 2-for-1 split, measured one day before the split.

Sample	N	Mean	10th	20th	30th	40th	50th	60th	70th	80th	90th
Panel A: Distribution of Prices for All Stocks											
1926 – 1970	540	34.98	9.69	13.70	17.77	22.12	26.84	32.32	38.95	48.61	66.23
1971 – 1990	240	20.60	6.71	8.58	10.70	13.12	15.81	19.03	23.17	28.71	37.92
1991 – 2004	168	33.29	6.79	8.91	11.44	14.19	17.19	20.79	25.41	31.69	42.56
Full Sample	948	31.03	8.43	11.55	14.86	18.44	22.34	26.91	32.56	40.58	54.87
Panel B: Distribution of Pre-Split Stock Prices											
1926 – 1970	819	67.43	38.62	46.00	52.00	57.63	62.50	68.50	75.63	84.50	100.00
1971 – 1990	2,302	48.08	22.13	29.75	35.50	39.75	44.00	49.38	55.38	63.63	77.00
1991 – 2004	2,303	63.83	29.50	37.38	43.50	49.25	55.15	62.13	71.88	84.75	105.25
Full Sample	5,424	57.67	27.00	34.75	40.25	45.75	51.44	57.50	65.50	76.00	93.13

Table 2
Price-Based Comovement Around Stock Splits

The table reports changes in the slope and the fit of regressions of returns for stocks conducting a 2-for-1 split on the returns of value-weighted price index portfolios. For each stock split, we estimate univariate and bivariate regressions separately for the one-year period before and after splits as follows:

$$R_{i,t} = \alpha_i + \beta_{LowPrc,i} R_{LowPrc,i,t} + \varepsilon_{i,t} ,$$

and

$$R_{i,t} = \alpha_i + \beta_{LowPrc,i} R_{LowPrc,i,t} + \beta_{HighPrc,i} R_{HighPrc,i,t} + \varepsilon_{i,t} .$$

$R_{i,t}$ is the return of stock *i* at time *t*, and $R_{LowPrc,i,t}$ and $R_{HighPrc,i,t}$ are low and high price index portfolios. The low price index contains stocks with prices within $[1/4\, p,\ 3/4\, p]$ and the high price index contains stocks within $[3/4\, p,\ 5/4\, p]$, where *p* is the pre-split price measured one day before the split. For the univariate regression, we report the average change in the coefficient around the split, and the average change in adjusted R-squared. For the bivariate regression, we report the average change in the coefficient for the low and high price indices. Standard errors are clustered by month. t-statistics are reported in parentheses. Panel A shows results for daily returns. Panel B shows results for weekly returns.

Sample	N	Univariate		Bivariate	
		$\overline{\Delta\beta_{LowPrc}}$	$\overline{\Delta\bar{R}^2}$	$\overline{\Delta\beta_{LowPrc}}$	$\overline{\Delta\beta_{HighPrc}}$
Panel A: Daily returns					
1926 – 1970	819	0.157	0.028	0.329	-0.191
		(8.69)	(4.53)	(9.36)	(-5.68)
1971 – 1990	2,302	0.204	0.023	0.316	-0.115
		(15.63)	(3.47)	(9.36)	(-3.70)
1991 – 2004	2,303	0.255	0.031	0.375	-0.127
		(11.31)	(5.26)	(7.90)	(-3.60)
Full Sample	5,424	0.219	0.027	0.343	-0.131
		(18.80)	(7.05)	(13.57)	(-6.43)
Panel B: Weekly returns					
1926 – 1970	819	0.107	0.043	0.269	-0.178
		(4.52)	(5.56)	(4.60)	(-2.99)
1971 – 1990	2,302	0.190	0.029	0.345	-0.160
		(10.19)	(3.68)	(6.35)	(-3.20)
1991 – 2004	2,303	0.221	0.027	0.394	-0.180
		(8.12)	(3.45)	(6.40)	(-3.59)
Full Sample	5,424	0.191	0.030	0.355	-0.171
		(13.07)	(6.27)	(9.84)	(-5.47)

Table 3
Price-Based Comovement Around Stock Splits: Fama-MacBeth
The table reports changes in the slope and the fit of regressions of returns of stocks conducting a 2-for-1 split on the returns of value-weighted price index portfolios. For each stock split, we estimate univariate and bivariate regressions separately for the one-year period before and after splits as follows:

$$R_{i,t} = \alpha_i + \beta_{LowPrc,i} R_{LowPrc,i,t} + \varepsilon_{i,t} \ ,$$

and

$$R_{i,t} = \alpha_i + \beta_{LowPrc,i} R_{LowPrc,i,t} + \beta_{HighPrc,i} R_{HighPrc,i,t} + \varepsilon_{i,t} \ .$$

$R_{i,t}$ is the return of stock i at time t, and $R_{LowPrc,i,t}$ and $R_{HighPrc,i,t}$ are low and high price index portfolios which are calculated as described in Table 2. For each month with at least one split, we take the cross-sectional mean of the changes in the slope coefficients $\Delta\beta_{LowPrc}$ and $\Delta\beta_{HighPrc}$, and then form the time-series average of the cross-sectional means. Standard errors are adjusted using Newey-West (1987) using 36 lags. t-statistics are reported in parentheses. Panel A shows results for daily returns. Panel B shows results for weekly returns.

Sample	N	Univariate	Bivariate	
		$\Delta\beta_{LowPrc}$	$\Delta\beta_{LowPrc}$	$\Delta\beta_{HighPrc}$
Panel A: Daily Returns				
1926 – 1970	253	0.199	0.374	-0.192
		(5.88)	(6.67)	(-5.51)
1971 – 1990	235	0.196	0.234	-0.040
		(11.41)	(4.35)	(-0.90)
1991 – 2004	157	0.232	0.319	-0.099
		(7.75)	(4.91)	(-2.21)
Full Sample	645	0.207	0.309	-0.114
		(12.32)	(8.44)	(-4.04)
Panel B: Weekly Returns				
1926 – 1970	253	0.139	0.265	-0.127
		(3.63)	(3.40)	(-2.31)
1971 – 1990	235	0.176	0.225	-0.057
		(6.86)	(2.83)	(-0.84)
1991 – 2004	157	0.210	0.343	-0.144
		(5.87)	(4.54)	(-2.37)
Full Sample	645	0.170	0.269	-0.105
		(8.26)	(5.70)	(-2.83)

Table 4
Price-Based Comovement Around Stock Splits: Comovement Relative to Matching Firms
The table reports changes in the slope and the fit of regressions of returns of stocks conducting a 2-for-1 split on the returns of value-weighted price index portfolios, relative to changes in the same estimates for matching stocks. Each stock in the event sample is matched with another stock on industry and growth in market capitalization over the pre-event estimation period. For each stock split and its respective matching firm, we estimate univariate and bivariate regressions separately for the one-year period before and after splits as follows:

$$R_{i,t} = \alpha_i + \beta_{LowPrc,i} R_{LowPrc,i,t} + \varepsilon_{i,t} \ ,$$

and

$$R_{i,t} = \alpha_i + \beta_{LowPrc,i} R_{LowPrc,i,t} + \beta_{HighPrc,i} R_{HighPrc,i,t} + \varepsilon_{i,t} \ .$$

$R_{i,t}$ is either the return of stock *i* at time *t* or the return of its respective matching firm, and $R_{LowPrc,i,t}$ and $R_{HighPrc,i,t}$ are low and high price index portfolios which are calculated as described in Table 2. For the univariate regression, we examine the average change in the slope around the split, and the average change in adjusted R-squared for stocks conducting a split minus the corresponding estimates for matching stocks. For the bivariate regression, we examine the average change in the slopes on the low and high price indices for stocks conducting a split minus the corresponding estimates for matching stocks. Standard errors are clustered by month. t-statistics are reported in parentheses. Panel A shows results for daily returns. Panel B shows results for weekly returns.

Sample	N	Univariate		Bivariate	
		$\Delta\Delta\beta_{LowPrc}$	$\Delta\Delta\bar{R}^2$	$\Delta\Delta\beta_{LowPrc}$	$\Delta\Delta\beta_{HighPrc}$
Panel A: Daily Returns					
1926 – 1970	766	0.165	0.011	0.361	-0.210
		(7.85)	(2.64)	(8.42)	(-5.04)
1971 – 1990	2,091	0.204	0.011	0.209	-0.005
		(14.94)	(4.18)	(6.01)	(-0.15)
1991 – 2004	2,072	0.186	0.010	0.289	-0.107
		(8.97)	(3.65)	(7.36)	(-3.13)
Full Sample	4,929	0.190	0.011	0.266	-0.079
		(17.34)	(6.11)	(11.44)	(-3.71)
Panel B: Weekly Returns					
1926 – 1970	766	0.116	0.009	0.284	-0.168
		(3.73)	(1.22)	(3.67)	(-2.16)
1971 – 1990	2,091	0.148	0.011	0.167	-0.016
		(5.82)	(2.38)	(2.97)	(-0.28)
1991 – 2004	2,072	0.219	0.017	0.145	-0.046
		(6.34)	(3.49)	(0.78)	(-0.64)
Full Sample	4,929	0.174	0.013	0.176	-0.054
		(9.18)	(4.33)	(2.13)	(-1.38)

Table 5
Price-Based Comovement Around Stock Splits: The Effects of Information Dissemination
The table reports changes in the slope and the fit of regressions of returns for stocks conducting a 2-for-1 split on returns of value-weighted price index portfolios, using five leads and lags. For each stock i, for daily frequency data, we estimate the univariate and bivariate regressions separately for the one-year period before and after splits as follows:

$$R_{i,t} = \alpha_i + \sum_{s=-5}^{5} \beta_{LowPrc,i}^{(s)} R_{LowPrc,i,t+s} + \varepsilon_{i,t} \, ,$$

and

$$R_{i,t} = \alpha_i + \sum_{s=-5}^{5} \beta_{LowPrc,i}^{(s)} R_{LowPrc,i,t+s} + \sum_{s=-5}^{5} \beta_{HighPrc,i}^{(s)} R_{HighPrc,i,t+s} + \varepsilon_{i,t} \, .$$

$R_{i,t}$ is the return of stock *i* at time *t*, and $R_{LowPrc,i,t}$ and $R_{HighPrc,i,t}$ are low and high price index portfolios which are calculated as described in Table 2. Standard errors are clustered by month. t-statistics are reported in parentheses. In Panel A, we report the mean difference between the pre-event and post-event Dimson beta.

Sample	N	Univariate		Bivariate	
		$\Delta\overline{\beta}_{LowPrc}$	$\Delta\overline{\bar{R}^2}$	$\Delta\overline{\beta}_{LowPrc}$	$\Delta\overline{\beta}_{HighPrc}$
1926 – 1970	819	0.067	0.023	0.110	-0.039
		(2.41)	(3.57)	(1.49)	(-0.54)
1971 – 1990	2,302	0.171	0.017	0.277	-0.114
		(7.16)	(2.28)	(4.40)	(-1.89)
1991 – 2004	2,303	0.198	0.015	0.273	-0.116
		(5.33)	(2.85)	(3.36)	(-1.54)
Full Sample	5,424	0.164	0.017	0.248	-0.103
		(8.88)	(4.17)	(5.65)	(-2.46)

Table 6
Determinants of the Change in Beta

The table reports coefficients from regressions of cumulative changes in the betas on a proxy for investor sentiment and firm characteristics. For each stock i, we estimate the bivariate regression separately for the one-year period before and after splits as follows:

$$R_{i,t} = \alpha_i + \beta_{LowPrc,i} R_{LowPrc,i,t} + \beta_{HighPrc,i} R_{HighPrc,i,t} + \varepsilon_{i,t} \; .$$

$R_{i,t}$ is the return of stock *i* at time *t*, and $R_{LowPrc,i,t}$ and $R_{HighPrc,i,t}$ are low and high price index portfolios which are calculated as described in Table 2. For each stock i, we create a measure of cumulative change in coefficients, $\Delta\beta_{cumulative} = \left(\Delta\beta_{lowPrc} - \Delta\beta_{highPrc}\right)$ and run the following regression:

$$\Delta\beta_{cumulative,i,t} = \alpha_i + \beta_{X,i} X_{i,t} + \varepsilon_{i,t} \; ,$$

where $X_{i,t}$ is one of the following variables: the *sf1* sentiment index as constructed by Baker and Wurgler (2006), the logarithm of the market capitalization in $ millions, the pre-split stock price, and the percentage of shares held by institutions. Standard errors are clustered by month. t-statistics are reported in parentheses. Panel A reports the results for daily data, and Panel B reports the results for weekly data.

Regression	Sentiment	Log(Size)	Pre-Split Price	Inst. Ownership	N	$\overline{R}^2$
Panel A: Daily Returns						
(I)	0.098 (2.42)				5,424	0.01
(II)		0.075 (3.93)			5,424	0.01
(III)			0.003 (2.71)		5,424	0.00
(IV)	0.089 (2.14)	0.069 (3.61)	0.001 (0.46)		5,424	0.01
(V)				-0.319 (-0.89)	1,198	0.00
Panel B: Weekly Returns						
(I)	0.178 (2.29)				5,424	0.01
(II)		0.089 (3.20)			5,424	0.01
(III)			0.003 (1.54)		5,424	0.00
(IV)	0.173 (2.20)	0.097 (3.19)	-0.001 (-0.60)		5,424	0.01
(V)				-0.149 (-0.26)	1,198	0.00

Table 7

Price-Based Return Correlation in the Cross Section: Pooled results

The table reports coefficients from stock-level time-series regressions of firm return on price and other indices. For each stock, we estimate the following regressions:

$$R_{i,t} = \alpha_i + \beta_{Prc,i} R_{Prc,i,t} + \beta_{Size,i} R_{Size,i,t} + \beta_{Ind,i} R_{Ind,i,t} + \beta_{Mkt,i} R_{Mkt,t} + \varepsilon_{i,t} \, ,$$

and

$$R_{i,t} = \alpha_i + \beta_{Prc,i} R_{Prc,i,t} + \beta_{DGTW,i} R_{DGTW,i,t} + \beta_{Mkt,i} R_{Mkt,t} + \varepsilon_{i,t} \, .$$

$R_{i,t}$ is the return of stock i. $R_{PRC,i,t}$ is the price index return, consisting of all stocks that are in the same price quintile but not in the same industry and/or size quintile, where size and price quintile are formed at the end of December of the previous years NYSE breakpoints. $R_{SIZE,i,t}$ is the size index return, consisting of stocks that are in the same size quintile but not in the same industry and/or the same price quintile. $R_{IND,i,t}$ is the industry index return, consisting of stocks that are in the same industry (using the 12 Fama and French industry classifications) but not in the same price and/or size quintile. $R_{Mkt,t}$ is the CRSP market return. $R_{DGTW,i,t}$ is the return for one of 125 characteristic benchmark portfolios return, based on size, book-to-market, and return momentum. All portfolios are value-weighted. For each stock-level time-series regression, we require at least one year of data. Overall, we have 10,750 stocks. The table reports the cross-sectional mean of the time-series coefficients. Cross-correlation and heteroskedasticity adjusted t-statistics are reported in parentheses. The sample period is 1974-2005. Panel A reports results for daily data. Panel B reports results for weekly data.

Regression	Price	Size	Industry	Market	DGTW
Panel A: Daily Returns					
(I)	0.379			0.369	
	(12.25)			(9.76)	
(II)	0.149	0.691		0.174	
	(8.17)	(29.69)		(7.70)	
(III)	0.379		0.279	0.074	
	(13.05)		(19.79)	(2.05)	
(IV)	0.158	0.709	0.239	-0.108	
	(9.39)	(31.73)	(19.61)	(-4.95)	
(V)	0.291			0.229	0.269
	(13.21)			(5.48)	(30.66)
Panel B: Weekly Returns					
(I)	0.442			0.440	
	(13.00)			(10.16)	
(II)	0.209	0.615		0.221	
	(9.95)	(25.20)		(8.37)	
(III)	0.460		0.365	0.024	
	(14.51)		(21.09)	(0.54)	
(IV)	0.234	0.636	0.331	-0.184	
	(12.01)	(27.18)	(21.63)	(-6.89)	
(V)	0.348			0.246	0.310
	(14.32)			(14.30)	(10.61)

Table 8
Price-Based Return Correlation in the Cross Section: Fama-MacBeth
The table reports the coefficient from stock-level time-series regressions of a stock's return on its respective value-weighted price index portfolio. We run the same regressions as in Table 7 with the exception that we run the stock-level time-series regressions separately for each year. Each year, we then take the cross-sectional mean of the time-series coefficients. The table reports the time-series mean of those cross-sectional means. We have 31 years of data. t-statistics are in parentheses. Panel A reports results for daily data. Panel B reports results for weekly data.

Regression	Price	Size	Industry	Market	DGTW
Panel A: Daily Returns					
(I)	0.281			0.480	
	(11.15)			(16.47)	
(II)	0.068	0.442		0.431	
	(7.31)	(26.43)		(20.27)	
(III)	0.272		0.282	0.207	
	(12.37)		(23.62)	(9.62)	
(IV)	0.082	0.484	0.231	0.141	
	(11.52)	(35.01)	(16.74)	(7.63)	
(V)	0.216			0.367	0.201
	(11.56)			(18.20)	(20.41)
Panel B: Weekly Returns					
(I)	0.296			0.578	
	(9.64)			(16.48)	
(II)	0.075	0.296		0.577	
	(5.44)	(12.65)		(19.39)	
(III)	0.323		0.374	0.171	
	(12.44)		(33.00)	(7.06)	
(IV)	0.126	0.391	0.324	0.105	
	(11.53)	(22.20)	(26.07)	(5.66)	
(V)	0.234			0.226	0.427
	(10.41)			(20.91)	(15.38)

Figure 1

Evolution of price-portfolio betas around stock splits.

The figure plots the mean slope coefficients from bivariate regressions of returns for stocks conducting a 2-for-1 split and for their respective matching stocks on the returns of value-weighted price index portfolios. For each stock split and its respective match, we estimate the bivariate regression

$$R_{i,t} = \alpha_i + \beta_{LowPrc,i} R_{LowPrc,i,t} + \beta_{HighPrc,i} R_{HighPrc,i,t} + \varepsilon_{i,t}$$

in rolling regressions over 12 months. $R_{i,t}$ is either the return of stock *i* at time t or the return of its matching firm, and $R_{LowPrc,i,t}$ and $R_{HighPrc,i,t}$ are low and high price index portfolios which are calculated as described in Table 2. The means of the split stock coefficients are plotted in event time on the left side and the means of the matching firm coefficients are plotted in event time on the right side. Panel A reports the results for daily data and Panel B reports the results for weekly data. For the split stocks, the plot also shows the coefficients from regressions of the split stock return on the value-weighted CRSP market return.