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Price-based return comovement ☆

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ABSTRACT

Similarly priced stocks move together. Stocks that undergo splits experience an increase in comovement with low-priced stocks and a decrease in their comovement with high-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, transaction costs, and return momentum. The results suggest that investors categorize stocks based on price.

1. Introduction

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 UK and US stock prices is too large to be fully explained by comovement in dividends.[1]

Recent research shows 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 Standard & Poor's 500 index begin to covary more with other members of the index, and Greenwood (2008) provides similar evidence for the Nikkei 225.[2] 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) show that correlated trading among retail investors leads to excess stock return comovement, and Pirinsky and Wang (2004) provide analogous 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

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

[2] In addition, Boyer (2007) studies the S&P/Barra Value and Growth stock indexes, which were created in 1992 and are constructed based on book-to-market cutoffs. He reports shifts in comovement for stocks that switch indexes, but finds the results do not hold prior to 1992 for stocks that would have switched had the indexes existed. The results suggest comovement among stocks with similar book-to-market ratios may be partially related to category investing.

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ways to changes in market sentiment (e.g., Baker and Wurgler, 2006), then as they move 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. In most economic settings prices play an essential role in the decision-making process. Stock prices are unique in that they can be changed arbitrarily by altering the number of shares outstanding. This practice 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 (2008) provide evidence that stock prices are important to investors. They show 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.

Price-based stock categorization 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., 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; 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 consider nominal prices to be important.[3]

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 low-priced stocks and a decrease in comovement with high-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. Perhaps most convincingly, the shift in comovement is not evident following the announcement of the split, but begins within days of the effective date.

The influence of nominal prices on stock return dynamics extends beyond the sample of firms that have recently split their shares. We construct price-based indexes using NYSE quintile breakpoints from the previous year and examine whether these portfolios explain returns in the full cross-section of stocks after controlling for common return factors. Regressing individual stock returns on the returns of non-overlapping portfolios based on price, firm size, book-to-market, industry, transaction costs, 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.

Is price-based comovement attributable to market frictions? Low-priced stocks tend to be less liquid and have smaller market capitalizations, which may deter investment from sophisticated traders and lead to clientele effects. For example, Gompers and Metrick (2001) show that institutional ownership is increasing in stock price and Kumar and Lee (2006) find that individuals tend to hold low-priced stocks. However, Mukherji, Kim, and Walker (1997) find that stock splits increase the numbers of both individual and institutional shareholders while leaving the fraction of institutional ownership unchanged. We find no relation between the level of institutional ownership and the shift in comovement following splits. Moreover, price-index portfolios continue to explain incremental variation in returns after eliminating stocks in the lowest NYSE price quintile, which suggests the findings are not driven by market frictions.

We next explore behavioral explanations. Investors may overemphasize the importance of nominal price in the decision-making process in part due to its availability. Research in cognitive psychology shows that people overweight information that is easily retrieved from memory when making decisions (Tversky and Kahneman, 1973). Given that nominal prices are cross-sectionally related to market capitalization, some investors may consider price to be a readily available proxy for firm size. We find the shift in comovement following splits is greater for large firms, which contrasts with the typical intuition that inefficiencies are greater for small firms but is consistent with the interpretation that investors mistakenly equate price with size.

Investors may also be prone to psychological heuristics that relate nominal prices to expected returns. For example, certain investors may perceive low-priced stocks as being closer to zero and farther from infinity, thus having more upside potential. For example, Kumar (2008) shows investors in socioeconomic groups that are more likely to invest in state lotteries gravitate towards low-priced stocks with their equity investments.[4] We find the shift in comovement following splits is greater during periods of high investor sentiment, which is consistent with the interpretation that some investors believe the

[3] 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.

[4] Anecdotal evidence for the "more upside" heuristic is found in an investor question submitted to *The Motley Fool*'s syndicated investment column. "With penny stocks, I can buy more shares per dollar than I can with more expensive stocks. Then when the shares go up, I'll make more money, right?" *The Chicago Sun-Times*, December 2, 2007.

Table 1
Descriptive statistics.
Data are from the Center for Research in Security Prices (CRSP), and include all ordinary common shares with a stock price greater than $5 over the period 1926–2004. 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

stock's lower post-split price increases its upside potential.

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 offer a straightforward justification for "trading range" motivations for splits and provide a potential explanation for the observed increase in volatility following splits.

The rest of the paper is organized as follows: Section 2 describes the sample, Section 3 presents evidence of shifts in price-based return comovement around stock splits, Section 4 extends the sample to all stocks and provides evidence of price-based return comovement in the full cross-section, Section 5 examines potential sources of price-based comovement, and Section 6 concludes.

2. Data and descriptive statistics

The data are from the Center for Research in Security Prices (CRSP) and include 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.[5] 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.[6] 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 (2008) also find stability in stock prices over time, and suggest that firms' splitting behavior presents a puzzle. Next, we investigate the extent to which investors categorize stocks based on price, which could provide a partial explanation for why firms split.

3. Price-based comovement: evidence from stock splits

We begin our analysis by examining price-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:

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

and

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

[5] We focus on 2-for-1 splits because it facilitates the formation of price-index portfolios. For splits greater than 2-for-1, the pre-split price is often so high that it is difficult to build portfolios of stocks with similar prices.

[6] 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.

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

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

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.[7] Equal-weighting the price-index portfolios rather than value-weighting produces similar results.

3.1. 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 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.

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^2, $\overline{\Delta\bar{R}^2}$. The results show an increase in both the low price-index coefficient and the adjusted R^2. 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^2 increases by roughly 3% for both daily and weekly returns. In comparison, Barberis, Shleifer, and Wurgler (2005) 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.

Ohlson and Penman (1985) and others show that stocks experience increased volatility following splits which would have a positive impact on the beta coefficient. We find above that the regression R^2 increases significantly following the split, which indicates that return correlation increases following the split. Specifically, average daily return correlation between the split stock and the low price portfolio is 0.34 before the split and 0.38 afterwards which represents an 11.8% increase. Thus, the increase in comovement is not driven by a change in risk following the split.[8]

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. Our sample includes all ordinary common shares with a stock price greater than \$5 over the period 1926–2004 conducting a 2-for-1 split. 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 $[1/4p, 3/4p]$ and the high price index contains stocks within $[3/4p, 5/4p]$, 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^2. For the bivariate regression, we report the average change in the coefficients for the low and high price indexes. 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)

[7] 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.

[8] Risk does generally increase following the split. For example, for weekly returns the standard deviation increases from 5.6% in the year before the split to 6.2% afterwards (the z-statistic for test of means is 7.9). However, the relation between price-based comovement and the increase in risk following splits could run the other way. If price-based categorization leads large, high-priced stocks to begin trading as if they were small following a split, one implication would be a higher return standard deviation. We analyze potential sources of price-based comovement in Section 5.

To more carefully control for changes in systematic risk following the split, we rely on a bivariate approach that includes low and high price portfolios. If investors categorize stocks based on price, subsequent to the split the stock will have a higher loading on the low price index and a lower loading on the high price index. The regression specification is:

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

Table 2 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.[9]

The decrease in the high price-index coefficient indicates that the shift in comovement is not driven by an increase in firm risk following the split. The regression coefficient on the high price index is equal to the covariance between the stock return of the split stock and the residual from regressing the high price portfolio on the low price portfolio, divided by the variance of the residual from regressing the high price portfolio on the low price portfolio. All else equal, an increase in firm risk should lead to an increase in the high price-index coefficient rather than a decrease, which suggests empirically the increase in firm risk is more than offset by a reduction in the correlation between stock returns and high price-index residual returns.

As a robustness check, we also use a Fama-Macbeth type approach. 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. The Fama-Macbeth results are qualitatively similar to those in Table 2 and not reported for the sake of brevity. For example, at the daily frequency the change in the low-price (high-price) beta is 0.309 (−0.114) with a t-statistic of 8.44 (−4.04), and the change in coefficients is significant in three of the four subperiods including the most recent period.

Another potential concern is that results may be driven by faster information diffusion following the event. Stock 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. The fact that we observe similar shifts in comovement using both daily and weekly data mitigates this concern. However, as an additional check we follow Dimson (1979), and Barberis, Shleifer, and Wurgler (2005) and re-estimate Eqs. (1) and (2) including five leading and lagging low price and high price-index returns. In untabulated results, we find the change in the sum of the coefficients on the current and lagged values of the low-price index is 0.248 (t-statistic equal to 5.65), and the change in the sum of the coefficients on the high price index is −0.103 (t-statistic equal to −2.46). The coefficients are similar in magnitude to the results in Table 2, which indicates that changes in the speed information diffusion are not driving the results.

3.2. 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, Shleifer, and Wurgler (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 the split firms and matching firms have complete returns data over the event horizon which reduces the sample to 4,929 splits. Requiring returns over the following 12 months for both the split stock and the matching firm mitigates the effects that survivorship bias may have on the results.

For the univariate regression, we examine the mean change in slope and the mean change in regression 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, $\overline{\Delta\Delta\beta_{LowPrc}}$

[9] An alternative methodology that has been suggested is to estimate a single regression for each stock surrounding the split with a dummy variable to denote the post-split period. Averaging the coefficients on the dummy variables across split firms produces results very similar to the change in betas reported in Table 2. Using daily data, at the individual regression level, 63% (55%) of the coefficients on the post-split dummies for the low (high) price indexes are positive (negative). Measuring significance at the 10% level, for the low (high) price indexes 18% (13%) of the dummy variables are significant with the right sign and 5% (7%) are significant with the wrong sign.

and $\overline{\Delta\Delta\beta_{HighPrc}}$. Again, standard errors are clustered by month.

Table 3 presents the results. The changes in the coefficients and adjusted R^2 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.

Fig. 1 extends the exercise in Table 3 to varying horizons around the split and depicts the evolution in price-index coefficients. The plots depict the mean average slope coefficients from the bivariate regression (2) for stocks conducting a split and for their respective matching firms. Regressions are run using daily and weekly data for two- to twelve-month horizons before and after split. Pre-split coefficients are estimated from return data before the split, and post-split coefficients are estimated from data after the split. For example, the coefficients reported at −2 months are estimated using data during the two months leading up to the split, the coefficients at −3 months rely on overlapping data during the three months before the split, etc. We also plot the mean coefficients from regressions of the split stock return on the value-weighted CRSP market return.

The figure confirms the results in Table 3. The split firms exhibit much larger shifts in betas than do the matching firms. Moreover, split stocks experience an upward trend in their comovement with high-priced stocks and a decreasing trend in comovement with low-priced stocks in the months leading up to the split, which is consistent with the general upward trend in prices preceding the event. Split firms enter the high price category roughly eight months before the split on average, and as is evident from Fig. 1, excluding returns nine to twelve months before the split strengthens the results.[10] The increase (decrease) in comovement with high price (low price) stocks leading up to the split is consistent with split firms being increasingly categorized as high-priced stocks.

Fig. 1 shows split stocks also experience an increase in market betas, which is consistent with Brennan and Copeland (1988). However, 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 not driven by a change in market beta.

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 typically 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.

Table 3

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. Our sample includes all ordinary common shares with a stock price greater than \$5 over the period 1926–2004 conducting a 2-for-1 split. 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. For the univariate regression, we examine the average change in the slope around the split, and the average change in adjusted R^2 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 indexes 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	
		$\overline{\Delta\Delta\beta_{LowPrc}}$	$\overline{\Delta\Delta\bar{R}^2}$	$\overline{\Delta\Delta\beta_{LowPrc}}$	$\overline{\Delta\Delta\beta_{HighPrc}}$
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)

[10] The results are no longer significant if we extend the window to three years before and after the split, but this is not surprising. The wider the length of the event horizon, the greater the period of time the stock tends to reside in the low price category both before and after the split.

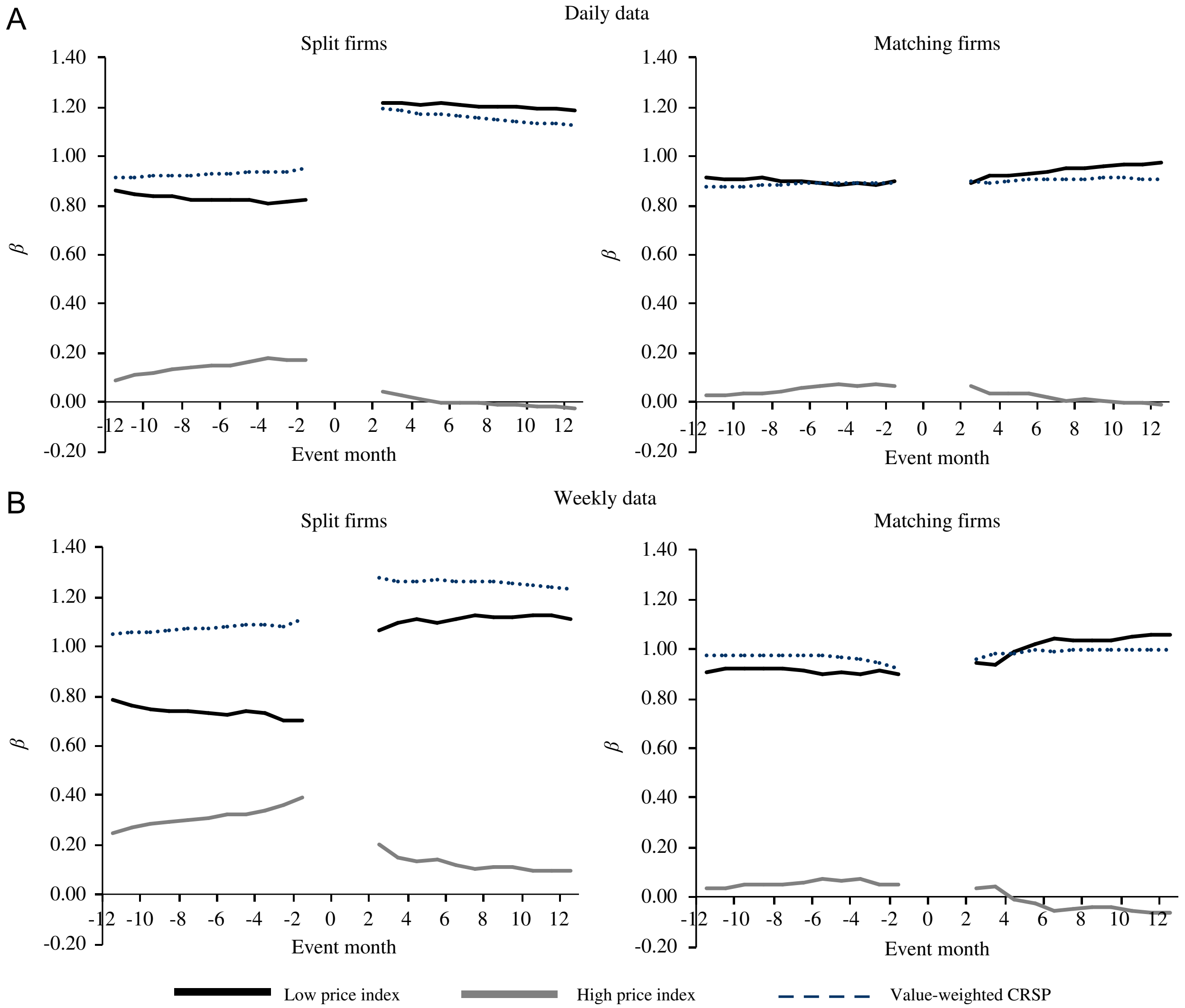

Fig. 1. Evolution of price-portfolio betas around stock splits. The figure plots the mean slope coefficients from bivariate regressions of returns for stocks conducting a 2-for-1 split and for their respective matching stocks on the returns of value-weighted price-index portfolios. Our sample includes all ordinary common shares with a stock price greater than $5 over the period 1926–2004 conducting a 2-for-1 split. For each stock split and its respective match, we estimate the bivariate regression:

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

$R_{i,t}$ 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. The low price index contains stocks with prices within $[1/4p, 3/4p]$ and the high price index contains stocks within $[3/4p, 5/4p]$, where p is the pre-split price measured one day before the split. Pre-split (post-split) coefficients are estimated with data before (after) the split using expanding windows with a minimum requirement of two months. 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. The plot also shows the coefficients from regressions of the split stock return and the matching stock return on the value-weighted CRSP market return. Panel A reports the results for daily data and Panel B reports the results for weekly data.

3.3. *Announcement vs. effective date*

Our final split test utilizes short-window regressions to investigate whether the shift in comovement reflects a change in fundamentals. Specifically, we analyze whether the change in comovement occurs at the announcement of the split, which should be the case if the split reveals fundamental information to the market, or later when the price change takes effect, which would support trading-based explanations. For this analysis we focus on the sample of splits with declaration dates in CRSP that take place between 15 days and one year before the effective date which results in 5,411 splits.

We calculate the change in price-index loadings during short intervals around the split. We measure the pre-announcement period beginning one year before the split to five days before the declaration period. The announcement period begins five days after the declaration date to five days before the effective date. On average there are 26 daily return observations in the announcement period regressions. For the event period we use increasing windows of 10, 20, 30, and 40 trading days with each beginning five days after the effective date.

The results are presented in Table 4. We find high-price (low-price) betas are significantly higher (lower) in the announcement period than in the pre-announcement period, which is inconsistent with the interpretation that the shift in comovement reflects a change in fundamentals that is revealed with the announcement. However, the shift in comovement is apparent within 10 days of the effective date (relative to the announcement period). Using the 40-day event window, the average change in beta from announcement period to event period is 0.369 for the low price index and −0.124 for the high price index with t-statistics of 6.13 and −2.51.

Together, the results indicate that after conducting a split, stocks quickly begin to covary more with low-priced stocks and less with high-priced stocks. Price-based comovement is not explained by changes in firm characteristics or increased speed of information diffusion, and the shift begins within days of the effective date rather than the announcement date. The results suggest that investors categorize stocks based on price.

Table 4
Price-based comovement around stock splits: Announcement vs. effective date.

The table reports changes in the slope coefficients from regressions of daily returns for stocks conducting a 2-for-1 split on the daily returns of value-weighted price-index portfolios. Our sample includes all ordinary common shares with a stock price greater than \$5 over the period 1926–2004 conducting a 2-for-1 split. For each stock split, we estimate univariate and bivariate regressions separately (1) from one year before the declaration date to five days before the declaration date (pre-announcement period), (2) from five days after the declaration date to five days before the effective date (announcement period), and (3) from five days after the effective date to either 10, 20, 30, or 40 trading days after the effective date (event period). The univariate and bivariate regressions are as follows:

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

and

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

We report the average changes in the coefficients for the low and high price indexes. Standard errors are clustered by month and t-statistics are reported in parentheses.

	Univariate	Bivariate	
	$\Delta\beta_{LowPrc}$	$\Delta\beta_{LowPrc}$	$\Delta\beta_{HighPrc}$
$\beta_{announcement} - \beta_{pre\text{-}announcement}$	0.055 (2.60)	−0.068 (−1.28)	0.116 (2.80)
$\beta_{event_{10days}} - \beta_{announcement}$	0.211 (4.26)	0.291 (2.11)	−0.087 (−0.76)
$\beta_{event_{20days}} - \beta_{announcement}$	0.262 (10.89)	0.329 (4.79)	−0.066 (−1.14)
$\beta_{event_{30days}} - \beta_{announcement}$	0.260 (12.60)	0.366 (5.79)	−0.107 (−2.08)
$\beta_{event_{40days}} - \beta_{announcement}$	0.249 (12.43)	0.369 (6.13)	−0.124 (−2.51)

4. Price-based return comovement: all stocks

In this section we examine whether the influence of nominal prices on stock return dynamics is evident in the full cross-section of stocks. Extending the sample beyond stock splits requires a new methodology to measure price categories. Specifically, we define price categories from January to December of year t using quintile breakpoints for 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 regressions:

$$R_{i,t} = a_i + \beta_{Prc,i} R_{Prc,i,t} + \beta_{Mkt,i} R_{Mkt,t} + \varepsilon_{i,t}, \tag{3}$$

where $R_{i,t}$ is the stock return of firm i at time t, and $R_{Prc,i,t}$ is the value-weighted 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 (1997) 12-industry classification), or in the same size quintile[11], or in the same transaction cost quintile.

We control for industry because certain price ranges might be more common in certain industries. We control for firm size and transaction costs since stock price tends to positively correlate with size and negatively correlate with transaction costs. Size quintiles are formed based on quintile breakpoints for the market capitalization of NYSE stocks at the end of December of the previous year. Estimates of effective transaction costs are obtained from Hasbrouck (2009) and we form analogous quintiles based on NYSE breakpoints for the previous year.[12] $R_{Mkt,t}$ is the value-weighted CRSP market return at time t. The market return is included in the regression to control for market-wide comovement.

To more thoroughly control for comovement related to firm characteristics other than price, we modify Eq. (3) by introducing value-weighted indexes related to size, industry, and transaction costs. Specifically, we estimate

$$R_{i,t} = \alpha_i + \beta_{Prc,i} R_{Prc,i,t} + \beta_{Size,i} R_{Size,i,t} + \beta_{Ind,i} R_{Ind,i,t} + \beta_{TC,i} R_{TC,i,t} + \beta_{Mkt,i} R_{Mkt,i,t} + \varepsilon_{i,t}, \tag{4}$$

where $R_{Size,i,t}$ is the value-weighted size index return, $R_{Ind,i,t}$ is the value-weighted industry return (using the

[11] The results hold if we also exclude stocks that are in adjacent size quintiles.

[12] Hasbrouck (2009) utilizes Bayesian techniques to estimate a generalized version of the Roll (1984) model to obtain yearly estimates of firm-level transaction costs from daily closing prices. He finds the approach produces estimates of effective transaction costs that correlate highly with those obtained from transaction data. The data can be downloaded from http://pages.stern.nyu.edu/~jhasbrou.

Fama and French 12-industry classification), and $R_{TC,i,t}$ is the value-weighted transaction cost index return for firm i during period t. We construct the portfolios to be non-overlapping. For example, the size index consists of all stocks that are in the same size quintile but not in the same industry, price, or transaction cost quintiles as stock i. Industry and transaction cost indexes are constructed in a similar manner.

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).[13] Stocks are assigned to 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:

$$R_{i,t} = \alpha_i + \beta_{Prc,i} R_{Prc,i,t} + \beta_{TC,i} R_{TC,i,t} + \beta_{DGTW,i} R_{DGTW,i,t} + \beta_{Mkt,i} R_{Mkt,i,t} + \varepsilon_{i,t}, \tag{5}$$

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

We first estimate Eqs. (3)–(5) 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 Eqs. (3) and (4) strengthens the results. Overall, we have 9,611 stocks. The standard errors are adjusted for cross-correlation and heteroskedasticity. To keep our analysis computationally feasible, we estimate the adjusted standard error only for weekly data and then use the weekly adjustment factor ($stderr_{no\ adjustment}/stderr_{with\ adjustment}$) to correct the standard errors for daily data. This adjustment is 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 5, the beta on the price category index is positive and highly significant in all cases. For daily returns, the average betas range from 0.096 to 0.255. For weekly returns, the average betas range from 0.151 to 0.324. In comparison, Pirinsky and Wang (2006) examine whether stocks in the same geographical area covary and estimate a time-series regression of monthly stock returns on a local index, industry index, and market index, and the coefficient on their local index is around 0.5.[14] If we include the same regressors in the weekly return regression, the coefficient on the price index is equal to 0.460. Thus, price-based comovement appears to be the same order of magnitude as the geographical-based comovement found in Pirinsky and Wang (2006).

As a robustness check, we also conduct 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 6. Again, the beta on the price category index is positive and significant

Table 5
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 value-weighted indexes. For each stock, we estimate the following regressions:

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

and

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

Price, size, industry, and transaction cost indexes are constructed to be non-overlapping portfolios. $R_{i,t}$ 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 exclusively (i.e., similar price but not in the same industry, size, or transaction cost quintile as stock i). Similarly, $R_{Size,i,t}$ is the size index return based on stock i's size quintile exclusively, $R_{Ind,i,t}$ is the industry index return using the Fama and French (1997) 12-industry classifications, and $R_{TC,i,t}$ is the transaction cost index return based on transaction cost quintiles using estimates from Hasbrouck (2009). Quintiles are formed at the end of December of the previous year using NYSE breakpoints. $R_{Mkt,t}$ is the CRSP market return. $R_{DGTW,i,t}$ is the return for one of 125 characteristic benchmark portfolio returns (as in Daniel, Grinblatt, Titman, and Wermers, 1997; and Wermers, 2004), based on size, book-to-market, and return momentum (excluding stocks with similar prices). All portfolios are value-weighted. Our sample includes all ordinary common shares with a stock price greater than \$5 over the period 1974–2005. For each stock-level time-series regression, we require at least one year of data. Overall, we have 9,611 stocks. The table reports the cross-sectional mean of the time-series coefficients. Cross-correlation and heteroskedasticity adjusted t-statistics are reported in parentheses. Panel A reports results for daily data. Panel B reports results for weekly data.

Regression	Price	Size	Industry	Trans. costs	Market	DGTW
Panel A: Daily returns						
(I)	0.255				0.507	
	(8.32)				(12.18)	
(II)	0.103	0.606			0.280	
	(5.67)	(23.56)			(8.78)	
(III)	0.254		0.223		0.276	
	(9.38)		(14.56)		(6.94)	
(IV)	0.211			0.263	0.291	
	(7.74)			(10.54)	(6.64)	
(V)	0.096	0.570	0.209	0.158	−0.076	
	(5.72)	(21.80)	(15.51)	(8.06)	(−2.51)	
(VI)	0.172			0.166	0.217	0.263
	(8.41)			(8.90)	(7.23)	(23.66)
Panel B: Weekly returns						
(I)	0.317				0.589	
	(9.33)				(12.56)	
(II)	0.151	0.537			0.341	
	(7.20)	(19.39)			(9.28)	
(III)	0.324		0.311		0.245	
	(10.46)		(17.01)		(5.11)	
(IV)	0.277			0.262	0.350	
	(9.24)			(7.93)	(6.25)	
(V)	0.154	0.517	0.302	0.148	−0.140	
	(7.68)	(19.16)	(17.78)	(5.47)	(−3.58)	
(VI)	0.235			0.128	0.262	0.304
	(10.23)			(5.11)	(6.56)	(23.38)

[13] The data are obtained from http://www.smith.umd.edu/faculty/rwermers.

[14] Although Pirinsky and Wang (2006) do not report the coefficient for their full sample, the coefficients in the three subperiods are 0.545, 0.532, and 0.459.

Table 6
Price-based return correlation in the cross-section: Fama-MacBeth.

The table reports coefficients from stock-level time-series regressions of firm return on price and other value-weighted indexes. Each year for each stock we estimate the following regressions:

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

and

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

Price, size, industry, and transaction cost indexes are constructed to be non-overlapping portfolios. $R_{i,t}$ 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 exclusively (i.e., similar price but not in the same industry, size, or transaction cost quintile as stock *i*). Similarly, $R_{Size,i,t}$ is the size index return based on stock *i*'s size quintile exclusively, $R_{Ind,i,t}$ is the industry index return using the Fama and French (1997) 12-industry classifications, and $R_{TC,i,t}$ is the transaction cost index return based on transaction cost quintiles using estimates from Hasbrouck (2009). Quintiles are formed at the end of December of the previous year using NYSE breakpoints. $R_{Mkt,t}$ is the CRSP market return. $R_{DGTW,i,t}$ is the return for one of 125 characteristic benchmark portfolio returns (as in Daniel, Grinblatt, Titman, and Wermers, 1997; and Wermers, 2004), based on size, book-to-market, and return momentum (excluding stocks with similar prices). All portfolios are value-weighted. Our sample includes all ordinary common shares with a stock price greater than $5 over the period 1974–2005. We average the coefficients each year and then across years. Panel A reports results for daily data. Panel B reports results for weekly data.

Regression	Price	Size	Industry	Trans. costs	Market	DGTW
Panel A: Daily returns						
(I)	0.210				0.583	
	(9.83)				(19.25)	
(II)	0.070	0.425			0.443	
	(7.21)	(32.10)			(22.10)	
(III)	0.197		0.238		0.363	
	(10.23)		(18.80)		(13.23)	
(IV)	0.155			0.157	0.501	
	(8.76)			(9.15)	(15.63)	
(V)	0.064	0.405	0.211	0.064	0.193	
	(9.06)	(31.45)	(16.52)	(5.38)	(7.99)	
(VI)	0.127			0.105	0.423	0.193
	(9.30)			(7.03)	(16.83)	(18.59)
Panel B: Weekly returns						
(I)	0.241				0.654	
	(8.88)				(18.77)	
(II)	0.083	0.319			0.544	
	(6.72)	(18.45)			(19.73)	
(III)	0.249		0.330		0.316	
	(10.33)		(26.31)		(10.81)	
(IV)	0.194			0.072	0.627	
	(8.08)			(3.83)	(16.60)	
(V)	0.104	0.346	0.302	−0.010	0.205	
	(9.95)	(22.26)	(26.29)	(−0.80)	(7.41)	
(IV)	0.164			0.017	0.525	0.206
	(8.78)			(1.10)	(17.20)	(21.35)

for all regressions and all data frequencies. For daily returns, the average betas range from 0.064 to 0.210. For weekly returns, the average betas range from 0.083 to 0.249. 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.

5. Sources of price-based return comovement

What leads investors to categorize stocks based on price? We first consider the role of market frictions. Low-priced stocks tend to be less liquid and have smaller market capitalizations, which may deter investment from institutional traders and lead to clientele effects. For example, Falkenstein (1996) shows mutual funds have an aversion to stocks priced less than $5 and Gompers and Metrick (2001) show that institutional ownership is increasing in stock price.[15] Analogously, Kumar and Lee (2006) find that retail investors tend to hold low-priced stocks. We exclude stocks priced below $5 throughout our analysis. Moreover, further excluding stocks with prices in the lowest NYSE quintile from the cross-sectional regressions above does not significantly weaken the results. Looking ahead to Table 7, we find a positive relation between firm size and the shift in comovement following splits and no significant relation for institutional ownership. Thus, although market frictions may exaggerate price-based return comovement they do not appear to be the driving force behind why investors categorize stocks based on price.

Institutional investors' preference for high-priced stocks may extend beyond fundamental considerations. We investigate this by sorting stocks based on size and price and examining levels of institutional ownership. In untabulated results, institutions display a preference for high-priced stocks even among the largest stocks. For example, institutions own 58.6% of shares on average for stocks in the middle size/highest price quintiles, yet only 53.6% of stocks in the largest size/lowest price size quintiles despite the latter group being almost ten times larger on average (market cap of $153M vs. $1,304M). The results suggest institutions may overemphasize price as a proxy for other stock characteristics such as size and liquidity.

We also examine changes in institutional ownership around splits.[16] Our results generally confirm the finding in Mukherji, Kim, and Walker (1997) that stock splits leave the overall fraction of institutional ownership unchanged. We find an insignificant increase in holdings of 0.37% with a *t*-statistic of 1.7. However, we find institutions do significantly increase their holdings of the matching firms (0.99% with a *t*-statistic of 4.05), and the difference between split firm and matching firm is significant (−0.61% with a *t*-statistic of −1.99). Thus, splits may deter institutions from purchasing the stock as it grows and increases its market value. Together, the institutional holdings results support the idea that institutional clienteles may play a role in price-based comovement that extends beyond friction-based explanations.

[15] Del Guercio (1996) suggests prudent man laws may prevent institutions from holding low-priced stocks.

[16] We calculate shares held by institutions as a fraction of shares outstanding. Requiring holdings data for the split and matching stocks for the quarters surrounding the split results in observations for 3,438 splits. Standard errors are clustered by quarter when calculating *t*-statistics.

Table 7
Determinants of the change in comovement.

The table reports coefficients from regressions of cumulative changes in the betas on a proxy for investor sentiment and firm characteristics. Our sample includes all ordinary common shares with a stock price greater than $5 over the period 1926–2004 conducting a 2-for-1 split. 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. For each stock split i, we create a measure of the cumulative shift in return comovement, $\Delta\beta_{cumulative} = (\Delta\beta_{lowPRC} - \Delta\beta_{highPRC})$, 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 *sf*1 market sentiment index as constructed by Baker and Wurgler (2006), the market capitalization decile based on NYSE breakpoints as of the end of December of the previous year, 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	Size decile	Pre-split price	Inst. ownership	N	$\bar{R}^2$
Panel A: Daily returns						
(I)	0.098				5,424	0.01
	(2.42)					
(II)		0.040			5,424	0.01
		(3.48)				
(III)			0.003		5,424	0.00
			(2.71)			
(IV)	0.103	0.033	0.001		5,424	0.01
	(2.47)	(2.83)	(0.95)			
(V)				−0.319	1,198	<0.01
				(−0.89)		
Panel B: Weekly returns						
(I)	0.178				5,424	0.01
	(2.29)					
(II)		0.037			5,424	0.01
		(1.92)				
(III)			0.003		5,424	<0.01
			(1.54)			
(IV)	0.185	0.039	0.000		5,424	0.01
	(2.34)	(1.73)	(0.12)			
(V)				−0.149	1,198	<0.01
				(−0.26)		

Small investors' preference for low-priced stocks is often explained by wealth constraints but behavioral explanations also may play a role. For example, Barber and Odean (2000) find in their sample of retail investors that the mean (median) household holds 4.3 (2.6) stocks worth $47,334 ($16,210), which is consistent with a wealth constraint only to the extent that investors prefer trading in round lots. Google Inc. provides anecdotal evidence that investors can adapt to higher nominal prices by trading in non-round lots. For example, during 2005 the price of Google rose from roughly $195 to $415 and the percentage of odd-lot trading grew from 6.8% to 11.2%. Thus, retail investors' tendency to hold low-priced stocks may reflect behavioral preferences regarding nominal prices more so than binding wealth constraints.

Investors may overemphasize the importance of nominal price in the decision-making process in part due to its availability. Research in cognitive psychology shows that people overweight information that is easily retrieved from memory when making decisions (Tversky and Kahneman, 1973). Given that nominal prices are cross-sectionally related to market capitalization, some investors may consider price to be a readily available proxy for firm size.

Certain investors may also be prone to psychological heuristics that relate nominal prices to expected returns. For example, some investors may perceive low-priced stocks as being closer to zero and farther from infinity, thus having more upside potential. Kumar (2008) suggests investors may consider low-priced stocks to have lottery-like features and finds that investors in socioeconomic groups that are more likely to invest in state lotteries gravitate towards low-priced stocks for their equity investments. In addition, Doran, Jiang, and Peterson (2008) find low-priced stocks do particularly well in January, which matches a similar seasonality in gambling activities in Las Vegas.

There is also anecdotal evidence that individual investors may believe low-priced stocks have more upside potential. Two mutual fund families (Fidelity and Royce) offer "Low-Price" stock funds geared towards retail investors that may appeal to this type of heuristic. Neither fund restricts its holdings to low-priced stocks, and independent investment researcher Morningstar Inc. describes the Fidelity Low-Priced Stock fund as a "marketing gimmick."[17]

5.1. Determinants of comovement following splits

We explore potential explanations for price-based comovement by examining the determinants of the shift in comovement around stock splits. Specifically, for each split we estimate the bivariate regression (2) separately for the period before and after the split and calculate the cumulative changes in beta $\Delta\beta_{cumulative} = (\Delta\beta_{lowPrc} - \Delta\beta_{highPrc})$. We use $\Delta\beta_{cumulative}$ as our measure of the shift in comovement following the split and regress this measure on a number of split characteristics.

If investors use price as a naïve proxy for firm size, we may expect a larger shift in comovement following splits for large firms. Nominal price and size tend to be related in the cross-section, which means small stocks will comove highly with low-priced stocks before the split and as a result have less of a potential for a shift. We include firm size in the comovement determinant regression, which we measure using NYSE deciles measured at the end of December prior to the split.

If some investors believe low-priced stocks have more upside potential, we may expect a greater shift in comovement following splits during periods of high market sentiment. Our measure of investor sentiment in the determinant regression 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.[18]

We conjecture that retail investors may be more likely to categorize stocks based on price. Small investors face greater difficulty in obtaining market information than professional investors and 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 to the disposition effect (detrimental tendency to sell winners and hold losers). A number of authors show that splits make stocks more attractive to small investors.[19] We hypothesize that a stock split will lead to a greater shift in comovement when the split stimulates incremental trading among retail investors. We expect a greater shift in comovement for stocks with higher pre-split prices where the split will lead to a larger price change, and a smaller shift for stocks that are widely held by institutions. We calculate institutional holdings as the proportion of shares held by institutions during the quarter before the split. Since the institutional holdings variable restricts the sample substantially, we regress the shift in comovement separately on the institutional holdings variable.

Table 7 presents the results of regressing the cumulative shift in comovement on characteristics of the split, where standard errors are clustered by month. The findings generally support behavioral explanations for price-based comovement over friction-based explanations. The shift in comovement following stock splits is significantly greater for large firms, which contrasts with the typical intuition that market inefficiencies are weaker for large firms but is consistent with the interpretation that investors overemphasize the link between nominal price and size. The fact that the shift in comovement is stronger for firms with large market capitalizations suggests large firms may be trying to appear small by splitting their stocks, as suggested by Baker, Greenwood, and Wurgler (2008).

The other main finding in Table 7 is that the shift in comovement following splits is significantly higher during periods of high market sentiment. The magnitude of the coefficient is 0.1 for daily and 0.19 for weekly, which implies 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 0.19, respectively. The result is consistent with the interpretation that some investors believe the split stock's lower post-split price increases its upside potential.

The perception of increased upside potential following a split is at odds with the pattern in return skewness. For example, weekly return skewness falls from 0.515 in the year before the split to 0.316 in the year after the split and the difference is highly significant (the *z*-statistic for test of means is 12.8). For the sample of splits with available matching stocks, weekly return skewness is 0.295 in the year after the split vs. 0.326 for matching firms (*z*-statistic is -3.95). The relatively low post-split skewness indicates that investors categorizing recently split stocks as if they have increased upside potential may be driven by behavioral factors rather than economic fundamentals.

We find modest evidence that the shift in comovement increases for firms with high pre-split prices, but the result appears mainly driven by size. The relation between the shift in comovement and institutional ownership is insignificant. Given that stocks that are widely held by institutions tend to be more efficiently priced, the lack of a significant relation between institutional ownership and the change in comovement suggests the results are not driven by market frictions. Together, the regression results in Table 7 suggest that investors overestimate the relation between nominal price and firm size when making investment decisions. The findings also offer support for the interpretation that certain investors believe low-priced stocks have more upside potential.

[17] http://mfb.morningstar.com 2/29/2008.

[18] 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 are from http://pages.stern.nyu.edu/~jwurgler.

[19] 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, and Zhu (2004) find increased retail trading following splits.

5.2. Additional evidence

In our final analysis, we offer additional evidence for the behavioral biases that may lead investors to categorize stocks based on price. We investigate the extent to which market participants consider low-priced stocks to have more upside potential by examining equity analysts' forecasts of long-term growth. Although professional analysts may be less likely to rely on price-based heuristics, a number of researchers have attributed inefficiencies in analysts' earnings forecasts to cognitive biases.[20] Moreover, analysts' long-term forecasts are not evaluated with the close scrutiny of earnings forecasts, which may allow for biases to play a greater role. For example, Dechow and You (2008) find that analysts are more likely to round long-term growth forecasts to the nearest multiple of five than they are for short-term forecasts.

Each month we run cross-sectional regressions of analysts' median long-term growth forecast on price, log size, log book-to-market, stock return over the previous year, firm age, and industry dummies based on two-digit SIC codes. We then average the coefficients across months from 1981 to 2007 and calculate standard errors using Newey West with 12 lags. In untabulated results, the mean coefficient on price is -0.010 and the t-statistic is -2.94. The coefficient suggests that after controlling for fundamentals, a one standard deviation increase in price leads to a 23 basis point lower median forecast of long-term growth.

Analysts are also more likely to raise their estimates of long-term growth in the one to three months following stock splits. We compare an individual analyst's most recent forecast of long-term growth made in the three months before the split to their first forecast made within three months after the split. Requiring analysts to issue long-term growth, forecasts in the three months before and after the split results in 978 observations. We find analysts increase their forecasts 56.1% of the time, and the z-statistic for a test that the ratio is greater than 0.5 is equal to 3.84. Narrowing the window to one month before and after the split or extending it to six months produces similar results.

Although the relation between nominal prices and analysts' forecasts of long-term growth is statistically robust, our interpretation is somewhat speculative since there may be alternative interpretations. For example, the increase in long-term growth forecasts after splits is also consistent with the signaling hypothesis, i.e., that splits signal managers' beliefs in strong future performance. However, empirical support for the signaling hypothesis is relatively weak. For example, Lakonishok and Lev (1987) report declining earnings growth in the three years following splits, and more recently Huang, Liano, and Pan (2006) find a negative relation between splits and future earnings after controlling for current profitability, market expectations about future earnings, and past dividend changes. Taken together, the positive relation between price and analysts' long-term growth forecasts, and the shift in forecasts around splits, supports the view that nominal prices may influence analysts when estimating a firm's growth prospects.

6. 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 explained by fundamentals, yet this interpretation hinges on their ability to fully control for economic influences such as local labor markets. 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 relatively 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 low-priced stocks and a decrease in comovement with high-priced stocks. The shift is not attributable to changes in fundamentals, firm characteristics such as size, or changes in liquidity or 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 a smaller pool of investors. Building on the results here, Baker, Greenwood, and Wurgler (2008) 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, transaction costs, book-to-market, and return momentum. Taken together, our

[20] See, for example, DeBondt and Thaler (1990) and Abarbanell and Bernard (1992). More recently, Kim, Lee, and Pantzalis (2006) argue that workplace incentives alone are not sufficient to explain analysts' optimism bias.

results emphasize the importance of investor sentiment for valuation, and suggest that nominal prices are relevant to investors when constructing and rebalancing their portfolios.

References

Abarbanell, J.S., Bernard, V.L., 1992. Tests of analysts' overreaction/underreaction to earnings information as an explanation for anomalous stock price behavior. Journal of Finance 47, 1181–1207.

Barber, B.M., Odean, T., 2000. Trading is hazardous to your wealth: the common stock investment performance of individual investors. Journal of Finance 65, 773–806.

Barberis, N., Shleifer, A., 2003. Style investing. Journal of Financial Economics 68, 161–200.

Barberis, N., Shleifer, A., Wurgler, J., 2005. Comovement. Journal of Financial Economics 75, 283–317.

Baker, M., Wurgler, J., 2006. Investor sentiment and the cross-section of stock returns. Journal of Finance 61, 1645–1680.

Baker, M., Greenwood, G., Wurgler, J., 2008. Catering through nominal share prices. Journal of Finance, forthcoming.

Benartzi, S., Michaely, R., Thaler, R.H., Weld, W.C., 2008. The nominal price puzzle. Unpublished working paper, University of California, Los Angeles.

Boyer, B.H., 2007. Comovement among stocks with similar book-to-market ratios. Unpublished working paper, Brigham Young University.

Brennan, M.J., Copeland, T.E., 1988. Beta changes around stock splits: a note. Journal of Finance 28, 1009–1013.

Dhar, R., Goetzmann, W.N., Shepherd, S., Zhu, N., 2004. The impact of clientele changes: evidence from stock splits. Unpublished working paper, Yale University.

Daniel, K., Grinblatt, M., Titman, S., Wermers, R., 1997. Measuring mutual fund performance with characteristic-based benchmarks. Journal of Finance 52, 1035–1058.

DeBondt, W.F.M., Thaler, R.H., 1990. Do security analysts overreact to information? American Economic Review 80, 52–57.

Dechow, P.M., You, H., 2008. What's in a nickel? Information flow and rounding in analyst forecasts. Unpublished working paper, University of California, Berkeley.

Del Guercio, D., 1996. The distorting effect of the prudent man law on institutional equity investments. Journal of Financial Economics 40, 31–62.

Dimson, E., 1979. Risk measurement when shares are subject to infrequent trading. Journal of Financial Economics 7, 197–227.

Doran, J.S., Jiang, D., Peterson, D.R., 2008. Gambling in the New Year? The January idiosyncratic volatility puzzle. Unpublished working paper, Florida State University.

Dyl, E.A., Elliott, W.B., 2006. The share price puzzle. Journal of Business 79, 2045–2066.

Easley, D., O'Hara, M., Saar, G., 2001. How stock splits affect trading: a microstructure approach. Journal of Financial and Quantitative Analysis 36, 25–51.

Falkenstein, E.G., 1996. Preferences for stock characteristics as revealed by mutual fund holdings. Journal of Finance 51, 111–135.

Fama, E.F., French, K.R., 1997. Industry costs of equity. Journal of Financial Economics 43, 153–193.

Froot, K.A., Dabora, E.M., 1999. How are stock prices affected by the location of trade? Journal of Financial Economics 53, 189–216.

Gompers, P.A., Metrick, A., 2001. Institutional investors and equity prices. Quarterly Journal of Economics 116, 229–259.

Greenwood, R., 2008. Excess comovement: evidence from cross-sectional variation in Nikkei 225 weights. Review of Financial Studies 21, 1153–1186.

Grinblatt, M., Keloharju, M., 2000. The investment behavior and performance of various investor-types: a study of Finland's unique data set. Journal of Financial Economics 55, 43–67.

Grinblatt, M., Keloharju, M., 2001. How distance, language, and culture influence stockholdings and trades. Journal of Finance 56, 1053–1073.

Hasbrouck, J., 2009. Trading costs and returns for US equities: estimating effective costs from daily data. Journal of Finance, forthcoming.

Huang, G.-C., Liano, K., Pan, M.-S., 2006. Do stock splits signal future profitability? Review of Quantitative Finance and Accounting 26, 347–367.

Kim, C., Lee, S., Pantzalis, C., 2008. Analyst forecast inefficiency in reaction to earnings news: Cognitive bias vs. economic incentives. Unpublished working paper, City University of Hong Kong.

Kumar, A., 2008. Who gambles in the stock market? Journal of Finance, forthcoming.

Kumar, A., Lee, C.M.C., 2006. Retail investor sentiment and return comovements. Journal of Finance 61, 2451–2486.

Lakonishok, J., Lev, B., 1987. Stock splits and stock dividends: Why, who, and when? Journal of Finance 42, 913–932.

Lee, C.M.C., Shleifer, A., Thaler, R.H., 1991. Investor sentiment and the closed-end fund puzzle. Journal of Finance 46, 75–109.

McNichols, M., Dravid, A., 1990. Stock dividends, stock splits, and signaling. Journal of Finance 45, 857–879.

Mukherji, S., Kim, Y.H., Walker, M.C., 1997. The effect of stock splits on the ownership structure of firms. Journal of Corporate Finance 3, 167–188.

Ohlson, J.A., Penman, S.H., 1985. Volatility increases subsequent to stock splits: an empirical aberration. Journal of Financial Economics 14, 251–266.

Pindyck, R.S., Rotemberg, J.J., 1993. The comovement of stock prices. Quarterly Journal of Economics 108, 1073–1104.

Pirinsky, C.A., Wang, Q., 2004. Institutional investors and the comovement of equity prices. Unpublished working paper, George Washington University.

Pirinsky, C.A., Wang, Q., 2006. Does corporate headquarters location matter for stock returns? Journal of Finance 61, 1991–2015.

Roll, R., 1984. A simple implicit measure of the effective bid-ask spread in an efficient market. Journal of Finance 39, 1127–1139.

Schultz, P., 2000. Stock splits, tick size, and sponsorship. Journal of Finance 55, 429–450.

Shiller, R., 1989. Comovements in stock prices and comovements in dividends. Journal of Finance 44, 719–729.

Tversky, A.N., Kahneman, D., 1973. Availability: a heuristic for judging frequency and probability. Cognitive Psychology 5, 207–232.

Wermers, R., 2004. Is money really 'smart'? New evidence on the relation between mutual fund flows, manager behavior, and performance persistence. Unpublished working paper, University of Maryland.