Confusion of Confusions: A Test of the Disposition Effect and Momentum

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Using investor-level data, I document that the disposition effect is absent following a stock split; inattentive investors may fail to split-adjust their reference point, confusing the winner versus loser status of their holdings. Consistent with the disposition effect impeding the incorporation of news, ex-date returns are significantly higher for split stocks with higher gains. However, the magnitude is small relative to momentum, and momentum remains robustly present among this sample of stocks void of the disposition effect. The results suggest that the disposition effect may slow the incorporation of news, but not to the extent that it alone explains momentum. (JEL: G11, G12, G14)

All things equal, investors have a greater propensity to sell winner stocks relative to loser stocks. This tendency, labeled the disposition effect by Shefrin and Statman (1985), is one of the most well-documented behavioral trading biases and has been found in individual and institutional investors in a variety of financial markets throughout the world. The disposition effect has lately gained validity as an explanation for many market anomalies. For example, Frazzini (2006) provides evidence that the disposition effect can slow the incorporation of news into prices, and Goetzmann and Massa (2008) show that the disposition effect can help explain stock volatility, returns, and trading volume. It has also garnered much attention as a possible driver of momentum. Grinblatt and Han (2005), as well as Weber and Zuchel (2002), develop models in which the disposition effect drives momentum in stock returns. Empirical support for this relationship includes Grinblatt and Han (2005) in the United States, and Shumway and Wu (2007) in international markets.

I appreciate helpful comments from André de Souza, Andrea Frazzini, Marcin Kacperczyk, Markku Kaustia, Anthony Lynch, Rik Sen, and seminar participants at the American Economic Association 2012 meeting, the Academy of Behavioral Finance and Economics Conference, the London Business School Trans-Atlantic Doctoral Conference, and NYU Stern. I especially thank Jeffrey Wurgler for helpful comments. I thank Terrance Odean for providing data. Send correspondence to Justin Birru, Fisher College of Business, The Ohio State University; telephone: (614) 688-1299. E-mail: birru.2@fisher.osu.edu.


2 Gabler (1998) also hypothesizes that the disposition effect may slow the incorporation of news into prices, but does not test this hypothesis.
Each of these theories relies upon the same fundamental model. Intuitively, disposition investors holding a stock for which good news causes an increase in value will sell the stock. This excess supply causes downward pressure on the stock price, resulting in a smaller initial price impact, and higher subsequent returns as the stock reverts to its fundamental value. A similar story applies to cases of bad news. After declines in value arising from bad news, investors will hold their shares, rather than sell. This reduces downward pressure on the stock price, preventing the price from fully incorporating the news. Subsequent returns will be consequently lower as the stock reverts to its fundamental value. Therefore, this investor behavior combined with the lack of perfectly elastic demand for stocks induces return predictability. The result is an underreaction to news, generating momentum in stock returns.

I find that the disposition effect breaks down following stock splits, likely because of a failure to properly update reference prices. Next, I utilize splits as an instrument to test theories linking the disposition effect to stock return anomalies. I find that, consistent with theory, split ex-date returns are largest for those stocks with the largest unrealized gains. However, despite the breakdown in the disposition effect in this postsplit sample of firms, momentum is robustly present, inconsistent with the disposition effect alone being the driver of momentum.

Many theories of the disposition effect rely upon investor formation of a reference price from which gains and losses are determined. I argue that the nominal change in stock prices caused by stock splits, coupled with investor inattentiveness to the split, leads to a breakdown in the disposition effect. Specifically, I contend that a breakdown in the disposition effect arises from investor failure to properly update their reference prices following the nominal share price decline caused by the stock split, resulting in investor confusion regarding the winner/loser status of the stock in question. I refer to this hypothesis as the nominal reference price hypothesis.3

Using individual investor trade-level data, I find that the disposition effect is substantially weakened following a split. I focus on the months after a split and find that those investors purchasing at a pre-split price no longer behave in accordance with the disposition effect; however, those investors purchasing at postsplit prices do still exhibit the disposition effect. Importantly, by exclusively focusing on investor holdings of splitting stocks, but exploiting variation in the date of purchase for identification, I am able to help rule out alternative stories, such as the possibility that investors fail to sell their gains following a split because they believe that the low postsplit price signals a large upside for the stock. The evidence is consistent with investors determining gains or losses based on a comparison of the current price with the actual unadjusted purchase

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3 The nominal reference price hypothesis is closely related to the finance literature on investor inattention (Bernard and Thomas 1996; Huberman and Kogan 1994; Levy and Zhang 1994; Lauter and Xiong 2000; Barber and Odean 2001; DellaVigna and Pollet 2009; Hirshleifer, Lim, and Teoh 2009; and Yuan 2015).
price, rather than the properly updated reference price that accounts for the split. As a result, in the case of forward splits (reverse splits), investors will often mistake gains (losses) for losses (gains), leading to the presence of a weakened disposition effect following splits.

The temporary breakdown in the disposition effect resulting from the demand shock to the subset of stocks undergoing splits provides a unique environment in which to examine the disposition effect as a driver of stock returns. If the disposition effect causes stock prices to underreact to news and deviate from fundamentals, then prices should fully revert to their fundamental values in the absence of the disposition effect. The result is that stocks with unrealized capital gains (stocks that by definition are trading at a price below their fundamental value) should see positive returns coinciding with this breakdown. The hypothesis that prices revert to their fundamental value in the absence of the disposition effect leads to a clear testable cross-sectional implication, namely, those stocks with the largest unrealized gains should experience the largest price response at the split ex-date. Additionally, if the disposition effect is the only driver of momentum, then the postsplit sample of stocks absent the disposition effect should be void of momentum.

I find that following the breakdown of the disposition effect arising from the stock split, stocks trading at a capital gain see a large one-time price jump in proportion to their unrealized gain, consistent with the disposition effect acting as a driver of returns in the manner suggested by theory. On the other hand, in the months following a split, momentum is present and is unable to be explained by the disposition effect, suggesting that the disposition effect is not alone in driving momentum.

The effects documented coincide with the change in nominal price occurring at the ex-date. While there is little evidence that splits signal expectations of strong future performance— for instance, Lakonishok and Levy (1987) and Asquith, Healy, and Palepu (1989) find little evidence that splits are correlated with future profitability and Huang, Liao, and Pan (2006) arrive at a similar conclusion using a more recent sample—that the effect documented here occurs at the ex-date rather than the announcement date also helps to rule out signaling explanations. Furthermore, a signaling story actually suggests that the inability of the disposition effect to explain momentum is particularly compelling evidence against the disposition effect driving momentum. This is because the signaling explanation suggests that postsplit abnormal returns reflect underreaction to the positive news that the split signals. The presence of momentum following splits therefore potentially reflects underreaction to news— exactly the phenomenon that the disposition effect is purported to explain. The inability of the disposition effect to explain momentum in this setting in which momentum is potentially driven by an underreaction to news can be taken as rather compelling evidence against the disposition effect being the driver of momentum.
The contributions of the paper are summarized as follows. To my knowledge, this is the first paper to (1) provide evidence that individual investors are inattentive to nominal changes in share price unrelated to fundamentals, (2) the first to link the stock split ex-date abnormal return to the disposition effect, and (3) the first to provide relatively direct evidence that the disposition effect is likely not the only determinant of momentum.

1. Predictions

The literature has typically attributed the disposition effect to imperfectly rational investor preferences, rather than to beliefs. Specifically, Kahneman and Tversky’s (1979) prospect theory has long been thought to be the underlying driver of the disposition effect; however, recent work by Barberis and Xiong (2009) and Kaustia (2010) has found prospect theory to be insufficient in explaining the disposition effect. Barberis and Xiong (2012) find that a model incorporating realization preferences is better able to explain the disposition effect, whereas Ben-David and Hirshleifer (2012) empirically find that the disposition effect does not seem to reflect a simple direct preference for realizing gains relative to losses per se. While the underlying cause of the disposition effect is not yet fully clear, what is clear is that the disposition effect does not seem to reflect fully rational behavior of investors. For example, Odean (1998) finds that this strategy is detrimental to investors; the future returns of the losing stocks that investors continue holding are worse than the future returns of the stocks that investors sell for a gain.

Many theories of the disposition effect rely upon investor formation of a reference price from which gains and losses are determined. This reference price is often taken to be the purchase price. If a stock has appreciated in value since purchase, its price will be greater than the reference price, and the investor will treat the stock as a winner. However, for a stock that undergoes a split, the purchase price ceases to be an accurate measure of the gain or loss accruing to an investor since purchase. In this instance, the current stock price cannot be compared to the purchase price when determining a gain or loss, and instead the investor must compare the current stock price to an updated reference price that accounts for the stock split. Alternately, speculative trading motives, which do not require reference price formation, also have been offered as potential explanations for the disposition effect. To the extent that investors naively infer changes in value from changes in nominal price, the implications for investor behavior will be similar to cases in which the disposition effect is dependent on psychologically important reference prices.

In the case in which the disposition effect is related to the winner/loser status of the stock, it is easy to see how investor failure to update reference prices could upset the disposition effect. For example, suppose that an investor purchases at $20 a stock that subsequently undergoes a 3:2 split. In this case, the nominal reference price from which the winner/loser status should be determined is
$13.33, rather than the $20 price at which the stock was purchased. If the investor is not cognizant of this split of one stock in her portfolio, and fails to adjust her $20 purchase price downward by the split factor, a “winner” stock likely will be incorrectly viewed as a loser. In this case the investor will be less willing to sell the stock than if she had properly adjusted her reference price for the stock split. In the case of a reverse split, an investor that fails to update her reference price will often mistake a loser for a winner. Again, an investor will not behave in accordance with the disposition effect, as now she will be more likely to sell than if she had properly adjusted her reference price.

The theory argues that the increased demand for stocks trading at a capital loss and the decreased demand for stocks trading at a capital gain caused by the disposition effect leads to a demand perturbation, causing prices to deviate from fundamental values. It is this demand perturbation that drives the predictability of stock returns. If the theory is correct, then the weakening of the disposition effect will lead to a smaller demand perturbation and prices partially reverting to their fundamental values. For stocks trading at a capital gain, the removal, or attenuation of the demand perturbation will translate into a positive stock price response, because the fundamental value is greater than the current price for stocks trading at a capital gain. In other words, the sudden increase in demand for splitting winner stocks relative to losers among disposition investors will result in a sudden jump in the stock price for stocks trading at a gain, as the demand perturbation from these investors is now decreased and the stock moves closer to its fundamental value. Grinblatt and Han (2005) incorporate the disposition effect into a model of demand for stocks. I will use this model as a framework to better understand the manner through which the sudden increase in demand by disposition effect investors for stocks trading at a capital gain will cause a contemporaneous price jump.

In the model of Grinblatt and Han (2005), the disposition effect (DE) is represented in investors’ demand function for stocks as

$$D^{DE} = 1 + b_t [(F_t - P_t) + \lambda (R_t - P_t)],$$

(1)

where $F_t$ is the fundamental value of the stock; $P_t$ is the price of the stock; $R_t$ is the reference price from which investors determine their gains or losses; $b_t$ is the slope of the rational component of the demand function; and $\lambda$ is a positive value that measures the relative importance of the capital gain component of demand.

This representation of the demand function captures the increased demand by disposition effect investors for stocks trading at a capital loss ($R_t > P_t$) and the decreased demand for those trading at a capital gain ($P_t > R_t$).

If investors fail to update their reference prices, then for any given stock, the proportion of investors viewing this stock as a gain following the split will be significantly lower than prior to the split. Because fewer investors now properly classify the stock as a gain following a split relative to before the split, the disparity in demand between winners and losers is now smaller than in the rest of the population of stocks, and the disposition effect is significantly
weaker for these stocks than others. In other words, a stock trading at a 20% gain relative to its aggregate cost basis will be realized at a far higher rate prior to the split than after the split, because fewer investors now classify it as a gain. Therefore, at the split date, there is a shift in the proportion of investors viewing the stock as a winner. Conversely, a stock trading at a 20% loss relative to its aggregate cost basis will be realized at about the same rate in the weeks following the split as in the weeks prior to the split.

In this model, \( \lambda \) captures the degree to which demand is influenced by the disposition effect. The decrease in the disparity in the rate at which gains are realized relative to losses would be captured by a decrease in \( \lambda \) at the time of the split, as the aggregate disposition effect is now decreased. This in turn would have price implications for splitting stocks experiencing this downward movement in \( \lambda \).

The rational investor’s demand function is modeled as
\[
D_t = 1 + b_t[(F_t - P_t)],
\]
and there is assumed to be a fixed supply of one unit of the risky stock. By aggregating investors’ demand functions, the model results in an equilibrium market price that is a combination of the fundamental value of the stock and the reference price:
\[
P_t = wF_t + (1 - w)R_t \quad \text{where} \quad w = \frac{1}{1 + \mu \lambda},
\]
and \( \mu \) is the fraction of DE investors.

As in Grinblatt and Han (2005), I maintain the assumption of a constant \( \mu \) across all stocks, as well as a constant unconditional \( \lambda \). The sudden decrease in \( \lambda \) at the date of the stock split, time \( t \), results in an increase in \( w \). By definition, stocks trading at a capital gain at the time of the split have a stock price that is below its fundamental value, and this will result in a jump in price as the demand distortion caused by the DE investors is lessened and the stock moves closer to its fundamental value at time \( t + 1 \).

In the remaining sections, I test the following hypotheses in turn:

(H1) Nominal disposition effect hypothesis: Investors no longer realize gains at a higher rate than losses following a stock split.

If investors fail to account for the change in nominal price caused by a split, they will be more likely to perceive gains as losses. This failure to properly adjust to the nominal change in share price will result in the breakdown of the disposition effect.

4 Alternatively one could imagine that \( \lambda \) is unchanged for the group of investors that are aware of the split (who therefore correctly update their reference prices), while \( \lambda \) becomes negative for those unaware. The implications are the same, as the result is an increase in \( w \), pushing the stock price closer to its fundamental value.

5 One could also model this as an increase in \( R_t \) for forward splits and a decrease in \( R_t \) for reverse splits. The implications are again the same as a change in \( \lambda \).
(H2) Reversion of prices to fundamentals: Stocks with the largest gains realize
the largest ex-date price jumps.

Theory suggests that the removal or dampening of the disposition
effect should result in market prices converging more quickly towards
their fundamental values. For stocks trading at a capital gain, this
translates into an increased force pushing the stock’s price higher than
would result normally. Stocks trading at a larger capital gain should see
a larger increase in price than those trading at a smaller capital gain.

(H3) Absence of momentum: In the absence of the disposition effect,
momentum should not be present.

This hypothesis follows immediately from the theory posited above.
If the disposition effect alone drives momentum, then momentum should
be absent in a sample of stocks void of the disposition effect. In the next
three sections I test hypotheses H1, H2, and H3, respectively.

2. Do Splits Disrupt the Disposition Effect?

2.1 Data and methodology

To directly test whether the disposition effect breaks down following nominal
changes in share price, I analyze the trading behavior of individual investors.
This analysis utilizes data introduced by Barber and Odean (2000). The data
are composed of trading activity for 78,000 households with accounts at a large
discount broker between January 1991 and November 1996. Data are available
on all purchases and sales of stocks during this period, as well as the price
at which the transaction is executed, quantity purchased or sold, and date of
transaction. For a detailed description, see Barber and Odean (2000).

To analyze the investor sell versus hold decision I follow the methodology
of recent disposition effect studies by Grinblatt, Keloharju, and Linnainmaa
(2012), Kaustia (2010), and Linnainmaa (2010). As in these papers, on each
day that a sale takes place in a portfolio of two or more stocks, I classify each
of the investor’s holdings as either a sell (1) or do not sell (0), and employ a
logit regression to model this discrete choice of the investor. The investor’s
sell versus hold decision is modeled as a function of the unrealized gain, and
a number of other variables that have been shown in the literature to impact the
sell decision of the investor. The baseline specification employed is

\[
\text{Sale}_{i,t} = \beta_0 + \beta_1 \text{Gain}_{i,t} + \beta_2 \text{Max}_{i,t} + \beta_3 \text{Min}_{i,t} + \beta_4 \text{December}_{i,t} \\
+ \beta_5 \text{December}_{i,t} \times \text{Gain}_{i,t} + \beta_6 \text{X}_{i,t} + \epsilon_{i,t}.
\] (4)

To capture the well-documented propensity of investors to sell gains at a higher
rate than losses, I include the indicator variable Gain. This variable takes
a value of one if a stock has appreciated in value since purchase and zero
otherwise. Gains and losses are counted on each day that an investor makes a
sale. Every time a stock is sold, I compare the selling price to the investor’s
average purchase price of the stock to determine whether it is a realized gain
or a realized loss. If there are multiple purchase dates, I calculate the purchase
price as the share-weighted average purchase price. For stocks that are in an
investor’s portfolio on the day of a sale, but are not sold, I obtain from CRSP
the closing price of the stock for that day to calculate the size of the gain or
loss that has accrued to the investor since purchase. I also take commissions
into account when determining gains or losses. When calculating gains and
losses on stocks that are not sold, I use the average commission per share
paid when the stock was purchased as the potential commission in the case
of a sale. Finally, stocks already in an investor’s portfolio at the start of
the data sample are excluded from the analysis, as the initial purchase price is not
available, making it impossible to determine the gain/loss status of the holding.

The disposition effect predicts that the coefficient on the Gain variable will take
a positive value, indicating that investors are more likely to sell gains.

\( \text{Min} (\text{Max}) \) takes a value of one if the stock is trading at its lowest (highest)
price relative to the past month. Past research predicts that both of these
variables will have positive coefficients as investors are more likely to sell
stocks at monthly highs or lows. A December dummy variable is included,
and is also interacted with the gain variable to capture the well-documented tax-
loss selling that takes place in December. Following Grinblatt and Keloharju
(2001), I include a long list of control variables. To control for past returns over
multiple horizons, I include the stock’s market-adjusted returns over multiple
non-overlapping past return horizons. To account for the potential asymmetry in
investor behavior regarding positive and negative returns, I include variables
to separately analyze positive market-adjusted returns and negative market-
adjusted returns over these past periods. These variables take the value max[0,
market-adjusted return] and min[0, market-adjusted return] over the specified
horizons. Specifically, the eleven different non-overlapping return horizons
relative to the sale decision are day 0, \(-1, -2, -3, -4, [-19, -5], [-39, -20],
[-59, -40], [-119, -60], [-179, -120], \) and \([-239, -180] \). In addition to the
market-adjusted return, I include a set of variables taking the value of the
index return over these same horizons. Finally, I interact \( \text{Gain} \) with each of
these thirty-three variables to control for the possibility that past returns induce
different behavior for winners and losers. In total there are sixty-six variables
included to fully control for past return behavior.

To control for volatility, I follow Grinblatt and Keloharju (2001) and include
the average squared return of the stock over the past fifty-nine trading days and
the average squared return of the market over this same past horizon. Variables
for the number of days since purchase and the days since purchase squared are

\[ \text{Grinblatt and Keloharju (2001), also find that Finnish investors are more likely to sell a stock that is trading at a}
\] monthly high or low. Heath, Huddart, and Livshits (1994) also find that employees are likely to exercise their stock
options when the stock is trading near its yearly high. In the case of mergers and acquisitions, Baker, Pan, and
Wurgler (2002) find that the 52-week high is a salient price that strongly influences the price offered by bidders.
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included to control for investor holding period. To account for differences in turnover, I include the stock’s one-month lagged turnover. Finally, I include a separate dummy variable for each month of the sample period, and three-digit SIC industry fixed effects.

2.2 Summary statistics

The split analysis includes both forward and reverse splits. However, reverse splits are not well represented in investor holdings, accounting for less than 1% of the total split observations. In both cases, H1 suggests that investors will fail to behave in accordance with the disposition effect following a split. In the case of a forward split, this is because investors may often confuse a winner for a loser. In the case of a reverse split, this is because investors may often confuse a loser for a winner. In both cases, Gain will fail to capture investor behavior in the manner hypothesized by the disposition effect.

Forward splits are defined as events with a CRSP distribution code of 5523 and a split ratio of at least 1.25-for-1. Reverse splits are defined as those with a split ratio less than 1-for-1. There are 1,916 distinct split events represented in the investor holdings. While reverse splits are included in the analysis, they make up less than 1% of the split sample. In the 30-day postsplit period, there are 43,017 instances of investors holdings of forward split stocks, but only 98 observations of reverse splits. This is not surprising given that reverse splits tend to occur after large drops in price, and therefore tend to be undertaken by much smaller companies. The median reverse split company in the holdings data has a market capitalization of about $37 million, whereas the median forward split holding over the sample period has a market cap of nearly $2 billion. Panel A of Table 1 displays summary statistics of all investor holdings, and panel B examines those holdings defined as splits. Splits are defined as holdings of forward or reverse splits in the 30-day period after a split and make up about 1.4% of the total sample of holdings. The average split size in the sample is about 1.9-for-1. Relative to the entire sample, splits are more likely to be classified as gains, more likely to be trading at a monthly high, and slightly less likely to be trading at a monthly minimum. Splits also tend to have shorter holding periods and higher returns in the past six months.

To isolate the effect of the split, the empirical analysis controls for a number of variables to account for differences that may exist between splitting stocks and non-splitting stocks. Of course, it is always possible that unobservable differences remain that may somehow lead to differential treatment of winners and losers between splitting stocks and those that have not split. To further help alleviate endogeneity concerns reflected in a firm’s choice to split, in some of the analyses that follow I also examine a sample that is confined to only splitting stocks. This further analysis exploits variation in the date of purchase within a split-only sample to better isolate the effect of stock splits on investors purchasing at pre-split prices. In doing so, I am able to compare two investors holding the exact same splitting stock on the same day who vary only in that
Table 1
Summary statistics

<table>
<thead>
<tr>
<th></th>
<th>Panel A: All stocks</th>
<th>Panel B: Split sample</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mean</td>
<td>Median</td>
</tr>
<tr>
<td>Gain</td>
<td>0.473</td>
<td>0</td>
</tr>
<tr>
<td>Min</td>
<td>0.087</td>
<td>0</td>
</tr>
<tr>
<td>Max</td>
<td>0.117</td>
<td>0</td>
</tr>
<tr>
<td>Ret_{t-6,t}</td>
<td>0.147</td>
<td>0.07</td>
</tr>
<tr>
<td>Mkt Cap (mm)</td>
<td>7,442</td>
<td>1,001</td>
</tr>
<tr>
<td>Turnover_{t-1}</td>
<td>0.167</td>
<td>0.09</td>
</tr>
<tr>
<td>Facpr</td>
<td>0.905</td>
<td>1</td>
</tr>
<tr>
<td>N(Splits)</td>
<td>8,645</td>
<td>1,416</td>
</tr>
</tbody>
</table>

This table gives summary statistics for stocks in investor portfolios on days on which a sale takes place. Panel A displays statistics for the entire sample. Panel B displays statistics for stocks that have undergone stock splits within the past 30 days. Gain takes a value of one for stocks that have appreciated in value since purchase. Min (Max) takes a value of one if a stock is trading at its lowest (highest) price relative to the past month. \( \text{Ret}_{t-6,t} \) is the stock’s return in the past six months. \( \text{Turnover}_{t-1} \) is turnover in month \( t-1 \). Facpr is the split factor from CRSP.

2.3 Results

Column 1 of Table 2 displays the baseline disposition effect results. The well-documented propensity for investors to realize gains at a higher rate than losses is reflected by the positive and significant coefficient on the Gain variable. The marginal effect in a logit regression is \( \frac{4}{3} \) of the estimated coefficient when the probability of success is \( \frac{1}{2} \). Therefore, the coefficient of 0.390 on the Gain variable indicates that a capital gain increases the probability of sale by about 10% from a point at which the propensity to sell is \( \frac{1}{2} \).

Column 2 examines H1. To test H1, the split variable focuses on those investors purchasing at a pre-split price level. Split is a variable taking a value of one for stocks that have split within the last 30 days, and have been purchased at least seven days prior to the ex-date. To capture whether investors properly update their reference prices and correctly classify gains, I include an interaction term between Split and Gain. The interaction term captures the additional willingness of investors to sell a stock trading at a capital gain that has just undergone a split. If some investors mistakenly classify gains as losses following the split, this will be reflected by a negative coefficient on the interaction term to offset Gain.

Sale decisions by the same investor are not likely to be independent. The same is potentially true at the stock level. To account for this, I cluster standard errors at the investor level and the stock level in all regressions presented in this section.

The coefficient on \( \text{Split} \times \text{Gain} \) represents the change in investor propensity to realize gains following a stock split. Consistent with investors failing to update their prices following a split, the negative coefficient on \( \text{Split} \times \text{Gain} \)
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Table 2
Sell versus hold decision

<table>
<thead>
<tr>
<th></th>
<th>1</th>
<th>2</th>
</tr>
</thead>
<tbody>
<tr>
<td>Gain</td>
<td>0.390***</td>
<td>0.391***</td>
</tr>
<tr>
<td></td>
<td>(0.009)</td>
<td>(0.009)</td>
</tr>
<tr>
<td>Split</td>
<td>0.054</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.041)</td>
<td></td>
</tr>
<tr>
<td>Split x gain</td>
<td>−0.366***</td>
<td></td>
</tr>
<tr>
<td>Controls</td>
<td>yes</td>
<td>yes</td>
</tr>
<tr>
<td>N</td>
<td>3,124,263</td>
<td>3,124,263</td>
</tr>
</tbody>
</table>

This table reports maximum likelihood regression coefficients and standard errors for logit regressions. The dependent variable is one when an investor sells a stock and zero when the stock is in the portfolio of an investor on the day a sale is made, but is itself not sold. Gain takes a value of one if the stock has appreciated in value since purchase. Split takes a value of one on the day of a stock split and the month after a stock split for stocks purchased at least seven days before a split. Unreported control variables include thirty-three return variables to capture different non-overlapping return horizons, these thirty-three return variables interacted with Gain, a December indicator variable, the December indicator variable interacted with Gain, variables to capture whether the stock price is at a monthly high or low, and controls for stock volatility, number of days since purchase, stock turnover, and month and industry fixed effects. Standard errors clustered at the investor level and stock level are in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

The results in Table 2 lend support to the nominal disposition effect hypothesis. The regressions control for a number of past return controls. It is, of course, possible that there is something unique in the price increase prior to split or unique to stocks that choose to split in particular that can not be captured by these past return variables or other controls. I next undertake a second test to provide further confirmation of the effect documented in Table 2.

In Table 3, the analysis is extended to examine two separate groups of holders of splitting stocks, those buying prior to the split, and those purchasing subsequent to the split. If investor inattentiveness to the split is leading investors to fail to properly update their reference prices, then there should be heterogeneity in investor behavior following the split. Specifically, those investors purchasing after the split will require no reference price updating to account for the split, as they have purchased at a postsplit price level. The nominal reference price hypothesis predicts that it should only be those investors purchasing at the pre-split nominal price that have their reference prices disrupted by the split, those purchasing at the postsplit nominal price should behave in accordance with the disposition effect. Furthermore, in holding constant the stock, and only varying the purchase date, I am able to help rule out the possibility that there is something distinct about stocks that split that might be driving the results. Rather, the evidence in Table 3 suggests

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7 The results are similar if I instead focus on the week after a split.
that it is the difference in the nominal price at purchase that is responsible for the results.

The regressions in Table 3 focus solely on the subsample of investors holding splitting stocks. In addition to all the variables specified in Table 2, a new set of variables is now added to determine if investors likely to be aware of the split, and those not purchasing at pre-split levels, behave differently than those less likely to be aware. New Split takes a value of one for the subset of investors holding postsplit that purchased subsequent to seven days prior to the ex-date. Old Split takes a value of 1 for the subset of investors holding postsplit that purchased more than seven days prior to the ex-date.

The results are shown in Column 1 of Table 3 and strongly support the nominal disposition effect hypothesis. The coefficient of 0.773 on New Split × Gain indicates that investors purchasing after the split do not display a weakened disposition effect, and in fact display a slightly stronger propensity to sell winners relative to losers in the sample of splitting stocks. On the other hand, the coefficient of 0.102 on Old Split × Gain is insignificant, indicating that among splits purchased prior to the split there is no increased propensity to sell winners relative to losers. Furthermore, the insignificant coefficient of −0.053 on New Split indicates that there is no difference in the unconditional
Table 4

<table>
<thead>
<tr>
<th>Nominal gain</th>
<th>1</th>
<th>2</th>
<th>3</th>
</tr>
</thead>
<tbody>
<tr>
<td>Gain</td>
<td>−0.196</td>
<td></td>
<td>−0.253*</td>
</tr>
<tr>
<td></td>
<td>(0.140)</td>
<td></td>
<td>(0.144)</td>
</tr>
<tr>
<td>Nominal gain</td>
<td>0.354**</td>
<td>0.405**</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.170)</td>
<td>(0.172)</td>
<td></td>
</tr>
<tr>
<td>Controls</td>
<td>yes</td>
<td>yes</td>
<td>yes</td>
</tr>
<tr>
<td>N</td>
<td>32,034</td>
<td>32,034</td>
<td>32,034</td>
</tr>
</tbody>
</table>

This table reports maximum likelihood regression coefficients and standard errors for logit regressions. The dependent variable is one when an investor sells a stock and zero when the stock is in the portfolio of an investor on the day a sale is made, but is itself not sold. Gain takes a value of one if the stock has appreciated in value since purchase. Nominal Gain takes a value of one if the stock has a nominal price that is larger than the nominal purchase price. Unreported control variables include thirty-three return variables to capture different non-overlapping return horizons; these thirty-three return variables interacted with Gain, a December indicator variable, the December indicator variable interacted with Gain, variables to capture whether the stock price is at a monthly high or low, and controls for stock volatility, number of days since purchase, stock turnover, and month and industry fixed effects. Standard errors clustered at the investor level and stock level are in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

likelihood of selling new split holdings relative to old holdings. These results are again consistent with the nominal reference price hypothesis that some investors purchasing prior to the split fail to update their reference prices due to inattention, and are therefore less likely to sell these stocks in the days after a split. However, those investors least likely to overlook the split, and those investors purchasing at a postsplit price level, do not suffer from this decreased propensity to sell gains relative to losses, and show no signs of a weakening of the disposition effect relative to the rest of the population of stocks.

Finally, Column 2 of Table 4 confirms that the results are not temporary. Additional variables are included to capture the behavior of investors purchasing at pre-split prices up to sixty days after the split. Consistent with the split permanently disrupting investor reference prices, investors purchasing at pre-split prices continue to fail to act in accordance with the disposition effect in the months subsequent to the split.

2.4 Nominal gains

One of the clearest implications of the nominal reference price hypothesis is that investors classify gains and losses based upon a comparison of the postsplit nominal share price with the nominal price at which the stock was purchased, rather than the split-adjusted price. To test this hypothesis, a new variable is introduced to capture whether a stock is trading at a nominal gain. Nominal Gain takes a value of one if the nominal price is greater than the nominal purchase price. Nominal Gain now better captures the behavior of an inattentive investor. That is, Nominal Gain captures whether an investor that fails to update her reference price will consider the holding as a gain or loss. Table 4 runs a horse race between Nominal Gain and Gain.
The sample now consists of only the pre-split purchaser sample, as these are investors with nominal purchase prices that are upset by the stock split. Column 1 displays the baseline results for the sample of pre-split purchases. The gain variable is negative, but insignificant, consistent with the earlier finding that investors do not behave in accordance with the disposition effect following a split. Column 2 includes the nominal gain variable without the gain variable. It is significant and of similar magnitude as the gain variable was in the earlier non-split full-sample regressions. Column 3 includes both Gain and Nominal Gain. The results provide further evidence that investors do fail to update reference prices following a split. Gain is again insignificant; now, however, Nominal Gain is significant and positive, suggesting that investors do seem to determine gains and losses from their unadjusted values when making sell decisions. The presence of a positive and significant coefficient again provides strong support for the nominal disposition effect hypothesis. In other words, investors are now only more likely to realize stocks that have appreciated in value if they also have a nominal share price greater than the nominal price of purchase. The outcome is that the majority of postsplit holdings that should be properly classified as gains will now be classified as losses, and as a result, in aggregate these true gains will be realized at a lower rate.

3. The Disposition Effect and Ex-Date Returns

Section 2 suggests that the disposition effect breaks down following a stock split, resulting in a sharp decrease in the propensity for investors to realize gains relative to losses subsequent to a split. Next, I examine whether the empirical evidence supports the disposition effect inducing return predictability in the manner predicted by H2.

To test H2, I examine the behavior of stocks trading at a capital gain at the time of a stock split. The model outlined in Section 1, coupled with the evidence in Section 2, implies that the price jump at the split date should be proportional to the size of the unrealized capital gain. For a similar decrease in λ, those stocks trading at the largest capital gain will see the largest upward price adjustments. Specifically, I expect to see a positive relationship between the ex-date return and the capital gains variable.

In the following analysis I turn from the use of investor-level data to the use of CRSP data. To test whether the disposition effect induces return predictability, I first define a measure of the unrealized capital gain. I follow Grinblatt and Han (2005) and define the unrealized capital gain as:

\[ g_{t-1} = \frac{P_{t-2} - R_{t-1}}{P_{t-2}}, \]  

(5)

8 The gain variable is winsorized at 2.5% and 97.5% to minimize the influence of outliers.
This table reports the summary statistics for the sample of NYSE and AMEX splits between 1967 and 2011 for which gains can be calculated. Market-adjusted returns are relative to the CRSP value-weighted index.

where \( P_t \) is the price of the stock at time \( t \) and \( R_t \) is the reference price from which investors measure their gain or loss. The aggregate reference price in this equation is defined as

\[
R_t = \sum_{n=1}^{260} \left( V_{t-n} \prod_{\tau=1}^{n-1} \left(1 - V_{t-n+\tau} \right) \right) P_{t-n},
\]

where \( V_t \) is the stock’s turnover ratio at time \( t \), and \( n \) is measured in weeks. The weight on \( P_{t-n} \) in the equation represents the probability that a stock purchased at time \( t-n \) has not been sold by time \( t \). The reference price thus computed represents an estimate of investors’ aggregate cost basis for the stock. All prices used in the reference price calculation are corrected for splits.

In order to assess the influence of the disposition effect in ex-date returns, I obtain from CRSP all stock splits occurring between 1967 and 2011. The analysis is limited to NYSE/AMEX firms, as volume numbers for NASDAQ firms do not allow me to obtain consistent estimates of reference prices. As in Grinblatt and Han (2005), I define a week to start on Thursday and end on the following Wednesday. At the beginning of the week of the split ex-date, I use the past five years of data to calculate the unrealized gain. Theory suggests that the shift in demand should result in a reversion to fundamentals for only those stocks trading at a capital gain, and as a result I restrict the sample to only those stocks with positive values of \( g_{t-1} \) at the time of the split. This analysis yields 4,230 splits for which the capital gains can be calculated and return data is available for the ex-date and following day. The summary statistics are presented in Table 6.

As a first step in examining the effect of the disposition effect on return predictability, I sort stocks into quintiles based on the size of the unrealized capital gain at the beginning of the week in which the split occurs. The two-day cumulative abnormal return \([0,+1]\) is reported across all quintiles. The results are shown in Table 6 for both raw and abnormal returns.

---

9 This results in the exclusion of less than 5% of the sample. As a result, the inclusion of these points does not change the results.
Table 6
Ex-date abnormal return

<table>
<thead>
<tr>
<th>Gain quintile</th>
<th>Raw return (%)</th>
<th>Market-adjusted abnormal return (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.4252</td>
<td>0.3222</td>
</tr>
<tr>
<td>2</td>
<td>0.8278</td>
<td>0.6956</td>
</tr>
<tr>
<td>3</td>
<td>0.8547</td>
<td>0.7754</td>
</tr>
<tr>
<td>4</td>
<td>0.9132</td>
<td>0.8910</td>
</tr>
<tr>
<td>5</td>
<td>1.8343</td>
<td>1.5548</td>
</tr>
<tr>
<td>5-1</td>
<td>1.2266***</td>
<td>1.2360***</td>
</tr>
<tr>
<td>t-stat</td>
<td>6.2441</td>
<td>6.9547</td>
</tr>
</tbody>
</table>

This table reports two-day returns sorted on unrealized gain. The sample period is 1967–2011 and consists of NYSE/AMEX splits of at least 1.25:1. Quintile 1 is formed from stocks with the smallest unrealized gains, whereas quintile 5 is made up of stocks with the largest unrealized past gains. Market-adjusted returns are relative to the CRSP value-weighted index. Standard errors are clustered by ex-date. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

The univariate analysis supports a role for the disposition effect as a driver of return predictability. The spread in returns between the top and bottom gains quintiles is large and in the direction of the hypothesized relationship, with stocks possessing larger unrealized gains experiencing larger returns at the event date. Both the raw and abnormal returns are increasing as one moves from the bottom to top quintile. The spreads in the raw and abnormal returns between the top and bottom quintiles are both greater than 1.20% over the two-day period, and both are statistically significant.

Table 5 shows that there is a large unconditional two-day ex-date return of about 1%. In the time since first being documented by Grinblatt, Masulis, and Titman [1984], few explanations have been given for the positive abnormal return accruing to investors on the ex-date of stock splits. However, to isolate the ability of the disposition effect to explain abnormal ex-date returns, the multivariate regressions in Table 7 control for the potential explanations that have been offered.

In Table 7 I regress the two-day abnormal return on the unrealized gain as of the beginning of the week, while including multiple controls for possible alternative hypotheses. I include an indicator variable that takes a value of one for an integer split factor, for example, a 2 for 1 split, and 0 for a non-integer split. Nayar and Rozeff [2001] argue that abnormal ex-date returns may arise as a result of trader inconvenience in trading the unsplit shares after the date of record, but prior to the ex-date, and that this may be aggravated by unsplit shares with non-integer split values. If this is the case, the ex-date return should be higher for non-integer splits, suggesting a negative relationship between abnormal return and integer splits.

Size is a measure of the market cap decile of the stock, with one being the smallest. Nayar and Rozeff [2001] argue that inconvenience may be greater for smaller stocks. Under this hypothesis, the coefficient on Size would be expected to be negative. In addition to these variables, I also include controls for the daily return variance in the 25-day period preceding the split announcement, as well as the mean daily turnover in the 25-day period.
Table 7
Ex-date abnormal return regressions

<table>
<thead>
<tr>
<th>Variable</th>
<th>Raw return</th>
<th>Market-adjusted abnormal return</th>
</tr>
</thead>
<tbody>
<tr>
<td>Gain</td>
<td>0.0220***</td>
<td>0.0247***</td>
</tr>
<tr>
<td></td>
<td>(0.0062)</td>
<td>(0.0056)</td>
</tr>
<tr>
<td>Integer split</td>
<td>−0.0017</td>
<td>−0.0015</td>
</tr>
<tr>
<td></td>
<td>(0.0013)</td>
<td>(0.0012)</td>
</tr>
<tr>
<td>Size</td>
<td>−0.0012***</td>
<td>−0.0015***</td>
</tr>
<tr>
<td></td>
<td>(0.0033)</td>
<td>(0.0033)</td>
</tr>
<tr>
<td>Variance</td>
<td>4.8657**</td>
<td>4.3730**</td>
</tr>
<tr>
<td></td>
<td>(1.9836)</td>
<td>(1.8569)</td>
</tr>
<tr>
<td>Turnover</td>
<td>−0.1312</td>
<td>0.0284</td>
</tr>
<tr>
<td></td>
<td>(0.1929)</td>
<td>(0.1675)</td>
</tr>
<tr>
<td>Record return</td>
<td>0.0147</td>
<td>0.0169</td>
</tr>
<tr>
<td></td>
<td>(0.0366)</td>
<td>(0.0348)</td>
</tr>
<tr>
<td>Low price premium</td>
<td>0.0149***</td>
<td>0.0107***</td>
</tr>
<tr>
<td></td>
<td>(0.0038)</td>
<td>(0.0034)</td>
</tr>
<tr>
<td>Delay</td>
<td>0.0002</td>
<td>0.0012</td>
</tr>
<tr>
<td></td>
<td>(0.0026)</td>
<td>(0.0025)</td>
</tr>
</tbody>
</table>

This table regresses two-day market-adjusted returns on unrealized gain and additional controls. The sample period is 1967–2011 and consists of NYSE/AMEX splits of at least 1.25:1. Integer Split takes a value of one for an integer split factor. Size is market capitalization decile with one being the smallest. Variance is equal to the daily return variance in the 25 days prior to the split announcement, whereas Turnover is equal to the mean daily turnover over this same period. Record Return is the return accruing on the record date. Low Price Premium is the log difference between the average market-to-book ratio of low-price firms and high-price firms. Delay is equal to one minus the ratio of $R^2$ from a regression of weekly return on contemporaneous market return to $R^2$ from a model of weekly return on contemporaneous market return and four lags of market return. Standard errors clustered by ex-date are in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

preceding the split announcement. I also control directly for the Nayar and Rozell (2001) inconvenience hypothesis by including Record Return, which measures the return accruing on the record day. The inconvenience hypothesis suggests that the record-date return and the ex-date return should be inversely related.

Baker, Greenwood, and Wurgler (2009) find that firms cater to investors by splitting to lower price levels when investors place higher valuations on low-price firms. To control for possible time-series variation in ex-date returns driven by investor demand, I include the low-price premium used by Baker, Greenwood, and Wurgler (2009) as a measure of investor demand for splitting stocks. Finally, Boehme and Danielsen (2007), find that in a univariate setting, market frictions help to explain ex-date returns. Following Boehme and Danielsen (2007) I use the Hou and Moskowitz (2005) market friction metric of price delay to capture this effect. Delay is equal to one minus the ratio of $R^2$ from a regression of weekly return on contemporaneous market return, to $R^2$ from a model of weekly return on contemporaneous market return along with four lags of market return.

10 The results are unchanged if I instead use their alternative catering proxies of the small-stock premium or average announcement effect of recent splits, or all three simultaneously.
The regressions in Table 7 confirm the results of the sorted quintile portfolios in Table 6. All of the controls enter with the expected sign. The results indicate a strong positive relationship between the unrealized gains and the magnitude of the two-day ex-date return. Table 7 displays regressions using both the raw return and market-adjusted return as dependent variables, and both show similar results. Gain is both statistically and economically significant. The magnitude of the coefficient (0.0247 in the market-adjusted return regression) is large. In the splits subsample, the mean of the gain variable in the bottom quintile of gains is 0.096, whereas in the top quintile it is 0.421, for a difference of 0.325. The multivariate regression results suggest that there is a $0.0247 \times 0.325\% = 0.80\%$ larger return accruing over the two-day period for splits in the top quintile relative to the bottom gains quintile as a result of the disposition effect. The results are consistent with the disposition effect impeding the incorporation of news and the removal of the disposition effect, leading to a reversion of prices to fundamental value.

Results of this economic magnitude cannot be explained by the Grinblatt and Han (2005) result documenting higher expected returns for stocks with larger capital gains. The coefficient of 0.0247 documented for the two-day period, versus that of Grinblatt and Han (2005) of 0.004 on a weekly basis, suggests an effect arising from the stock split that is about $(0.0247 \times 2.5)/0.004 = 15.5$ times larger than that documented by Grinblatt and Han (2005).

The evidence thus far is consistent with the behavioral hypotheses suggesting that the disposition effect impedes the incorporation of news and induces return predictability. The results suggest that the sudden increase in demand for gains relative to losses does in fact cause prices to further align with their fundamental value, affecting prices in the manner predicted by theory. In Section 4 I turn to H3. While the evidence presented here is consistent with the disposition effect being a contributor to return anomalies, such as momentum and postevent drift, I next provide evidence that the momentum effect is larger than can be explained by the disposition effect alone, suggesting that the disposition effect is not the only driver of momentum.

4. Does the Disposition Effect Drive Momentum?

The empirical results documented above are consistent with models that advocate the ability of the disposition effect to drive return predictability, but they cannot determine the degree to which the disposition effect drives momentum. The finding in Section 2 documenting the failure of the disposition effect to explain investor behavior following nominal changes in stock price provides an opportunity to test the extent to which the disposition effect is responsible for momentum. The presence of momentum following stock splits would be inconsistent with a model relying solely on the disposition effect.

To address this question, I utilize CRSP data and employ an empirical methodology similar to that of Grinblatt and Han (2005).
Confusion of Confusions

use weekly MiniCRSP data on NYSE/AMEX firms to examine the ability of the disposition effect to explain momentum in a sample of firms over the period 1967–1996. I aggregate CRSP daily data to weekly data, defining a week as beginning on Thursday and ending on the following Wednesday, as is done in the MiniCRSP database used by . I initially extend their study to 2011, employing a similar sample of firms and using the same methodology. model expected returns as a monotonically increasing function of unrealized capital gains. They empirically analyze this relationship by estimating the following Fama-MacBeth (1973) regressions of weekly returns:

\[ r = \alpha_0 + \alpha_1 r_{-4} - 1 + \alpha_2 r_{-52} - 5 + \alpha_3 r_{-156} - 53 + \alpha_4 V + \alpha_5 s + \alpha_6 g, \] (7)

where \( r_{-t_1 \cdots t_2} \) is the cumulative return from week \( t_1 \) through \( t_2 \); \( V \) is the average weekly turnover ratio over the prior fifty-two weeks; \( s \) is the natural log of market capitalization in thousands of dollars; and \( g \) is the capital gains variable defined in Equation (5).

To ensure that I have gathered a sample comparable to theirs, I first replicate the main results from , while extending their sample to 2011. The results are in Table 8. Grinblatt and Han’s model suggests that if the disposition effect is the driver of momentum, then a variable capturing the aggregate capital gain for a stock should predict returns. The intermediate horizon return is likely to be highly correlated with this capital gains variable, and therefore serves as a noisy proxy for such a variable. If this is the case, then the capital gains variable of Equation (5) should be more effective than the intermediate horizon return variable in predicting returns.

The results in Table 8 are consistent with those of Grinblatt and Han and with their argument in favor of the disposition effect as an explanation for momentum. Results are shown separately for all months and for February through December. Columns 1 and 2 document the standard findings in the momentum literature. There is a short and long-term reversal effect. There is also a clear intermediate-horizon momentum effect when the capital gains variable is excluded from the regression in the first two columns.

In Columns 3 and 4, the capital gains variable is added to capture the disposition effect. The addition of this variable eliminates the significance of the intermediate-horizon momentum effect. The capital gains variable becomes highly significant in this regression and the sign of the coefficient is consistent with the prediction of Grinblatt and Han’s (2005) model.

If momentum is caused solely by the disposition effect, then the absence of the disposition effect following a stock split should result in the absence of momentum. For this reason, the absence of the disposition effect following stock splits provides an opportunity to test the extent to which the disposition effect influences momentum. Clearly, the use of CRSP data does not allow me to determine if postsplit holders of a stock purchased their shares before or after the split. The use of Fama-MacBeth weekly cross-sectional regressions as in
This table updates and replicates the main results of Grinblatt and Han (2005). The table tests the ability of the disposition effect to explain the presence of momentum in a sample of NYSE and AMEX firms between July 1967 and December 2011. Stock returns in week $t$ are regressed on the following variables: $r_{t-1}$ is the cumulative return from week $t-1$ through $t-2$; $V$ is the average weekly turnover ratio over the prior 52 weeks; $s$ is the natural log of market capitalization in thousands of dollars; and $g$ is the capital gains variable defined in Equation (5). Columns 1 and 2 examine the presence of the intermediate-horizon momentum effect in stock returns. Columns 3 and 4 include the capital gain variable in the regression to analyze the ability of the disposition effect to explain momentum. Regression results are reported for all months, and separately for February–December. Standard errors are in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

<table>
<thead>
<tr>
<th>Variable</th>
<th>All Feb–Dec</th>
<th>All Feb–Dec</th>
</tr>
</thead>
<tbody>
<tr>
<td>$r_{t-1}$</td>
<td>-0.0372***</td>
<td>-0.0353***</td>
</tr>
<tr>
<td>$r_{t-2}$</td>
<td>(0.0012)</td>
<td>(0.0012)</td>
</tr>
<tr>
<td>$r_{t-52}$</td>
<td>0.0007*</td>
<td>0.0015***</td>
</tr>
<tr>
<td>$r_{t-156}$</td>
<td>(0.0004)</td>
<td>(0.0004)</td>
</tr>
<tr>
<td>$V$</td>
<td>-0.0439***</td>
<td>-0.0534***</td>
</tr>
<tr>
<td>$s$</td>
<td>(0.0148)</td>
<td>(0.0153)</td>
</tr>
<tr>
<td>$g$</td>
<td>0.0001</td>
<td>0.0002***</td>
</tr>
</tbody>
</table>

This table updates and replicates the main results of Grinblatt and Han (2005). The table tests the ability of the disposition effect to explain the presence of momentum in a sample of NYSE and AMEX firms between July 1967 and December 2011. Stock returns in week $t$ are regressed on the following variables: $r_{t-1}$ is the cumulative return from week $t-1$ through $t-2$; $V$ is the average weekly turnover ratio over the prior 52 weeks; $s$ is the natural log of market capitalization in thousands of dollars; and $g$ is the capital gains variable defined in Equation (5). Columns 1 and 2 examine the presence of the intermediate-horizon momentum effect in stock returns. Columns 3 and 4 include the capital gain variable in the regression to analyze the ability of the disposition effect to explain momentum. Regression results are reported for all months, and separately for February–December. Standard errors are in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Grinblatt and Han (2005) also results in a trade-off between sample size and time proximity to a split. To ensure that I have enough split observations for weekly Fama-MacBeth regressions, while still focusing on a window adequately close to the stock split, I look at splits occurring within the previous two months (eight weeks). To keep the ex-date effect documented in Section 3 from biasing the results, I define week 1 as the first week not including the ex-date or day after the ex-date.

The aggregate reference price variable is created using the past 260 weeks of price data. By extending my sample to include splits that have occurred up to two months ago, I am including some investors who have purchased the stock postsplit (and therefore should not suffer from any confusion resulting from the nominal price change) in the calculation of the reference price. However, because under this definition of the reference price the majority of prices used in calculating the reference price are pre-split, the impact of including these postsplit investors in the calculation of the reference price should be relatively small. In any event, the inclusion of these investors should only bias the sample against finding any results suggesting that investors suffer errors in accounting for stock splits. Despite these slight limitations to an analysis using CRSP data, the results are rather clear.

In Table 9, I replicate the regressions from Table 8 while including two additional variables. I interact $r_{t-52}$ with an indicator variable taking a value of one if the stock has split within the past two months. I also include a separate indicator for stocks that have not split within this time period. Included in Columns 3 and 4 are two separate gains variables defined analogously to the return variables just discussed. Specifically, the regression equation being tested...
Table 9

Fama-MacBeth cross-sectional split regressions (1967–2011)

<table>
<thead>
<tr>
<th>Variable</th>
<th>All Feb–Dec</th>
<th>All Feb–Dec</th>
</tr>
</thead>
<tbody>
<tr>
<td>( r_{t-4} )</td>
<td>-0.0371**</td>
<td>-0.0348**</td>
</tr>
<tr>
<td></td>
<td>(0.0015)</td>
<td>(0.0014)</td>
</tr>
<tr>
<td>( r_{t-52} \times l_{split} )</td>
<td>0.0033**</td>
<td>0.0030**</td>
</tr>
<tr>
<td></td>
<td>(0.0012)</td>
<td>(0.0013)</td>
</tr>
<tr>
<td>( r_{t-52} \times l_{nosplit} )</td>
<td>0.0014***</td>
<td>0.0024***</td>
</tr>
<tr>
<td></td>
<td>(0.0004)</td>
<td>(0.0003)</td>
</tr>
<tr>
<td>( r_{t-156} )</td>
<td>-0.0005***</td>
<td>0.0002</td>
</tr>
<tr>
<td></td>
<td>(0.0002)</td>
<td>(0.0001)</td>
</tr>
<tr>
<td>( V )</td>
<td>-0.0609***</td>
<td>-0.0884***</td>
</tr>
<tr>
<td></td>
<td>(0.0173)</td>
<td>(0.0188)</td>
</tr>
<tr>
<td>( s )</td>
<td>-0.0001</td>
<td>0.0004***</td>
</tr>
<tr>
<td></td>
<td>(0.0001)</td>
<td>(0.0001)</td>
</tr>
<tr>
<td>( g \times l_{split} )</td>
<td>0.0014</td>
<td>0.0031</td>
</tr>
<tr>
<td></td>
<td>(0.0016)</td>
<td>(0.0039)</td>
</tr>
<tr>
<td>( g \times l_{nosplit} )</td>
<td>0.0032***</td>
<td>0.0050***</td>
</tr>
<tr>
<td></td>
<td>(0.0005)</td>
<td>(0.0005)</td>
</tr>
</tbody>
</table>

The table tests the ability of the disposition effect to explain momentum in the two months following a stock split. The sample is composed of NYSE and AMEX firms between July 1967 and December 2011. Stock returns in week \( t \) are regressed on some combination of the following variables: \( r_{t-1} \) through \( r_{t-52} \) is the cumulative return from week \( t-1 \) through \( t-52 \); \( V \) is the average weekly turnover ratio over the prior 52 weeks; \( s \) is the natural log of market capitalization in thousands of dollars; \( g \) is the capital gains variable defined in Equation (5); and \( l_{split} \) takes a value of one for any stock that has experienced a split in the past two months. Columns 1 and 2 examine the presence of the intermediate-horizon momentum effect in stock returns. Columns 3 and 4 include the capital gain variable in the regression to analyze the ability of the disposition effect to explain momentum. All distributions with a split factor of at least 0.1 are defined as splits. Only weeks with at least ten occurrences of stocks having split within the past two months are included. Regression results are reported for all months, and separately for February–December. Standard errors are in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

in Columns 3 and 4 is

\[
r = \alpha_0 + \alpha_1 r_{t-4} + \alpha_2 r_{t-5} \times l_{split} + \alpha_3 r_{t-52} \times l_{nosplit} + \alpha_4 r_{t-156} \times l_{split} + \alpha_5 V + \alpha_6 s + \alpha_7 g \times l_{split} + \alpha_8 g \times l_{nosplit} + \alpha_9 \times l_{split}.
\] (8)

Columns 3 and 4, test for the presence of momentum in the postsplit sample, and whether this is captured by the disposition effect.

The regressions in the first two columns show that there is a strong intermediate-horizon momentum effect in the postsplit sample, as well as in the entire sample. In fact, the momentum effect is stronger in the postsplit sample than it is in the rest of the population of stocks. Columns 3 and 4 examine the presence of the intermediate-horizon momentum effect after the capital gains variable is introduced to capture the disposition effect. In the postsplit sample the capital gains variable fails to gain significance, consistent with the findings in Section 2, and importantly, the momentum effect is still present in the postsplit sample of firms. The strong presence of momentum in the postsplit sample, despite the absence of the disposition effect, indicates that there is likely more to the story of momentum than the disposition effect.

Finally, I analyze an even smaller window following the split. Table 10 relies upon sorts to determine the explanatory power of the disposition effect in the 4 weeks following a split. Given that high gain stocks are likely to also be
Table 10
Weekly returns for portfolios sorted by gain residual

<table>
<thead>
<tr>
<th></th>
<th>Weekly returns %</th>
<th>N (weeks)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 (low residual)</td>
<td>0.149</td>
<td>2,133</td>
</tr>
<tr>
<td>2</td>
<td>0.211</td>
<td>2,133</td>
</tr>
<tr>
<td>3</td>
<td>0.235</td>
<td>2,133</td>
</tr>
<tr>
<td>4</td>
<td>0.247</td>
<td>2,133</td>
</tr>
<tr>
<td>5 (high residual)</td>
<td>0.304</td>
<td></td>
</tr>
<tr>
<td>High minus low</td>
<td>0.155**</td>
<td></td>
</tr>
</tbody>
</table>

Panel B Split sample

<table>
<thead>
<tr>
<th></th>
<th>Weekly returns %</th>
<th>N (observations)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 (low residual)</td>
<td>0.463</td>
<td>2,916</td>
</tr>
<tr>
<td>2</td>
<td>0.449</td>
<td>3,282</td>
</tr>
<tr>
<td>3</td>
<td>0.228</td>
<td>3,315</td>
</tr>
<tr>
<td>4</td>
<td>0.361</td>
<td>3,400</td>
</tr>
<tr>
<td>5 (high residual)</td>
<td>0.408</td>
<td>3,748</td>
</tr>
<tr>
<td>High minus low</td>
<td>−0.054</td>
<td>(0.36)</td>
</tr>
</tbody>
</table>

This table reports weekly returns for portfolios sorted on the residual from a regression of the form
\[ g = \alpha_0 + \alpha_1 r_{t-4} + \alpha_2 r_{t-5} + \alpha_3 r_{t-156} + \alpha_4 V + \alpha_5 s. \]

The sample period is July 1967–December 2011. At the beginning of each week \( t \), stocks are sorted into five equally weighted portfolios based on the capital gain residual. The sample consists of all NYSE/AMEX stocks that have the necessary data to estimate the regression. The results are for February–December. Panel A shows the results for the full sample of stocks. Panel B shows for only those observations occurring in the four weeks subsequent to the week of the stock split. All distributions with a split factor of at least 0.1 are defined as splits. \( t \)-statistics are in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

those experiencing high past returns, I would like to control for past returns and other variables influencing returns when assessing the impact of the gains variable. To do so, stocks are sorted based on a capital gains residual, which is the residual from the regression specified in Equation (9):
\[ g = \alpha_0 + \alpha_1 r_{t-4} + \alpha_2 r_{t-5} + \alpha_3 r_{t-156} + \alpha_4 V + \alpha_5 s. \] (9)

In Table 10 stocks are sorted according to the capital gains residual. This table documents the ability of gains to predict returns after controlling for multiple past return horizons as well as for size and past turnover. Panel A shows the results for the full sample of stocks. As is documented in prior work, the gains residual has additional explanatory power in explaining returns, consistent with the theory that the disposition effect drives momentum. However, the same is not true for the sample of splitting stocks in panel B. The results here indicate that the gains variable has no power in predicting returns in this sample of stocks. The results in panel B are consistent with the finding in Section 2 that the disposition effect weakens following splits. These findings again support the hypothesis that the disposition effect is not alone in driving momentum.

\[11\] I have also rerun the results using an unadjusted “nominal” gains variable in place of the gains variable for split stocks. The results are unchanged as this variable is also unable to explain momentum in the postsplit sample.
5. Conclusion

There is a growing literature documenting the limited attention of investors. The evidence presented here suggests the presence of a further example of investor inattention, namely, the inability of investors to properly identify and account for changes in nominal share price arising from stock splits. I find that prior to stock splits, investors behave in a manner consistent with the disposition effect; however, following a stock split, investors exhibit very little difference in the rates at which they realize gains and losses. The result is that the disposition effect breaks down for stocks that have recently split.

In the past fifteen years a number of behavioral theories have been proposed to explain the presence of momentum. These include well-known work by Barberis, Shleifer, and Vishny (1998), Daniel, Hirshleifer, and Subrahmanyam (1998) and Hong and Stein (2000). The disposition effect is the latest behavioral explanation for momentum, and has received much attention in the past few years.

The second half of this paper examines the extent to which the disposition effect is responsible for momentum by taking advantage of this sample of stocks displaying a vastly reduced disposition effect. Grinblatt and Hart (2005), Frazzini (2006), Shumway and Wu (2007), and Goetzmann and Massa (2008), among others, have documented the ability of the disposition effect to impede the incorporation of news and induce return predictability. Consistent with these findings, I find that a breakdown in the disposition effect appears to result in stock prices converging toward their fundamental values, as I infer from the ex-date. However, I also find that although the disposition effect is virtually absent following a split, momentum is still present in this sample. While not denying that the disposition effect may play a role in momentum, the evidence here also suggests that it is not the full story.

References


Barberis, Shleifer, and Vishny (1998) show that a model incorporating representativeness and conservatism can explain momentum, post earnings announcement drift, and long-run reversal. Daniel, Hirshleifer, and Subrahmanyam (1998) show that a model incorporating investor overconfidence with biased investor self-attribution can deliver short-run momentum and long-term reversals. Hong and Stein (2000) deliver underreaction in the short run and overreaction in the long run by modeling a market with two separate groups of agents, one group that observes private information, but is unable to extract all private information because of information frictions, and another group made up of momentum traders.


Confusion of Confusions


