Can the Market Multiply and Divide?
Non-Proportional Thinking in Financial Markets

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Abstract

We hypothesize that investors partially think about stock price changes in dollar rather than percentage units, leading to more extreme return responses to news for lower-priced stocks. Consistent with such non-proportional thinking, we find a doubling in price is associated with a 20-30% decline in volatility and beta (controlling for size and liquidity). To identify a causal effect of price, we show that volatility increases sharply following stock splits and drops following reverse splits. Lower-priced stocks also respond more strongly to firm-specific news of the same magnitude. Non-proportional thinking helps to explain a variety of asset pricing patterns such as the size-volatility/beta relation, the leverage-effect puzzle, and return drift and reversals.

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1 Introduction

When evaluating how a piece of news should affect stock prices, rational investors should think in percentage terms rather than nominal dollar terms. Holding the equity size of a stock constant, the nominal share price has no real meaning, because the price depends on the arbitrary number of shares a firm's equity is divided into. However, dollar price changes in reaction to news are ubiquitously reported and discussed. For decades, newspapers such as the Wall Street Journal only published dollar price changes for stocks. More recently, popular stock-tracking applications, like the one pre-installed on the iPhone, have shown dollar price changes by default. Also, television networks such as CNBC routinely display tickers showing dollar price changes (see Figure 1 for examples). This emphasis on nominal price changes may both cause and reflect a tendency of investors to (at least partially) think that a given piece of news should correspond to a certain dollar change in price rather than a certain percentage change in price. In other words, investors may engage in non-proportional thinking.

To fix ideas, consider two otherwise *identical* stocks of the same size, one trading at \$20/share and another trading at \$30/share. Investors who think in dollar terms may believe that the same piece of good news, such as the arrival of a highly skilled CEO, should correspond to a \$1 increase in price for both stocks.[1] Such non-proportional thinking would lead to a greater return response for the lower-priced stock than for the higher-priced stock. Similarly, with the arrival of additional news over time, non-proportional thinking would lead to greater return volatility for the lower-priced stock than the higher-priced stock, even if the two stocks were subject to the same sequence of news. These predictions apply broadly to all types of news that move stock prices. This includes news about cash flows as well as news about discount rates; it also includes firm-specific news as well as news that is aggregate in nature. To the extent that market returns reflect aggregate news, non-proportional thinking would also lead the returns of lower-priced stocks to move more strongly with the market, leading them to have higher market betas.

We begin by testing the volatility predictions implied by non-proportional thinking. We find

[1] For example, the investor may recall that, when a firm announced the arrival of a new skilled CEO, its share price increased by \$1. When a different firm announces similar news, the investor mistakenly reasons that the new firm should also experience a \$1 increase in share price.

that lower nominal share price is associated with higher total return volatility, as well as higher idiosyncratic volatility and market beta. The economic magnitudes are large: a doubling in share price corresponds to a 20—30 percent reduction in these three measures of volatility. Of course, the negative relation between volatility and price could be attributable to other factors. In particular, small-cap stocks are known to have higher total volatility, idiosyncratic volatility, and market beta, possibly because small-cap stocks are fundamentally more risky. Small-cap stocks also tend to have lower nominal share prices, so the price-volatility relation in the data could be driven by size. However, we find that the negative price-volatility relation remains equally strong after introducing flexible controls for size. Moreover, the negative relation between size and volatility flattens by more than 80% after we introduce a single control variable for nominal share price. Similarly, the well-known negative beta-size relation in the data flattens toward zero after controlling for price. Thus, non-proportional thinking may explain the size-volatility and size-beta relations rather than the reverse. In addition, we show that non-proportional thinking can explain the "leverage effect" puzzle in which volatility is negatively related to past returns (e.g., Black, 1976; Glosten, Ravi, and Runkle, 1993). As prices decline, volatility increases because investors react to news in dollar units and thereby more strongly in percentage units.

Overall, we find that price has extremely high explanatory power for volatility in a manner that matches the predictions of a non-proportional thinking framework. The negative volatility-price relation remains stable in magnitude after controlling for other potential determinants of volatility such as volume turnover, bid-ask spread percentage, market-to-book ratio, leverage ratio, and sales volatility. The results hold in the cross-section as well as in panel regressions that control for time-invariant stock characteristics. The results also hold in the recent time period and within a subsample limited to large-cap stocks. We also show that the results cannot be explained by tick-size limitations that constrain absolute dollar price changes to be above some minimum. In addition, we find that the magnitude of the volatility-price relation declines with institutional ownership and size, suggesting that the volatility-price relation represents a form of mispricing that is weaker among stocks that are easier to arbitrage.

While this collection of facts is consistent with non-proportional thinking, it remains possible that an omitted factor may drive the negative relation between price and volatility. To better account for potential omitted factors, we study how volatility changes around stock splits. Following a standard 2-for-1 stock split, the share price falls by 50%. While the occurrence of a split in a given quarter is unlikely to be random (e.g., firms often choose to split their stock following good performance), the fundamentals that drive the split decision are likely to be slow-moving since all splits are pre-announced, usually by one month ahead of the split execution date. Our tests only require that firm fundamentals do not change on the split execution date. We find a sharp discontinuity around stock splits: total return volatility, idiosyncratic volatility, and market beta increase by approximately 30 percent immediately after a 2-for-1 split. Further, the volatility does not return to pre-split levels, even after six months.

To better account for endogenous pre-trends that can drive split activity, we adopt a difference-in-differences strategy that compares 2-for-1 splits (in which the price drops by 50%) and 3-for-2 splits (in which the price drops by 33%). By comparing these two types of splits, we can control for common factors that might accompany both types of positive splits, while isolating a causal effect of the additional drop in share price associated with 2-for-1 splits. Moreover, we find that volatility decreases sharply when prices rise in the case of reverse splits (e.g., when 2 shares become 1 and price increases).

We also show that our results cannot be explained by changes in investor bases or media coverage. Previous research has argued that lower prices, and splits in particular, may attract speculative retail investors, who could drive up volatility (e.g., Brandt et al., 2009). Along the same lines, media coverage of firms usually increases around splits, which could contribute to volatility. We examine detailed data on retail and institutional investor ownership and trading patterns, and find that splits are associated with a small shift toward retail investors and a temporary increase in the buying activity of retail investors. However, these factors cannot generate the sharp, large, and persistent change in volatility that we document.

In the remainder of the paper, we directly explore how return responses to news events vary with share price. We identify news events in several ways. First, we identify news events through textual analysis using data from Boudoukh et al. (2018). On days where Boudoukh et al. (2018) identify value-relevant news events for stocks, we find that lower-priced stocks experience more extreme returns, consistent with non-proportional thinking. Of course, it is possible that lower-priced stocks simply tend to have more extreme news events. However, our analysis in this case is limited to S&P 500 stocks due to data coverage. Among this set of large firms, it seems plausible that the distribution of news events would be similar across levels of nominal price.

Next, we study how return responses to quarterly earnings announcements vary with share price. On earnings announcement days, we find that lower-priced stocks experience more extreme returns. Again, it is possible that lower-priced stocks tend to have more extreme earnings news. However, in this case, we can control for the extremity of the news using the standardized earnings surprise relative to analyst forecasts. We find that the absolute magnitude of the return response to the same earnings surprise decreases with a stock's price prior to the announcement. Thus, lower-priced stocks respond more strongly initially to the same news, consistent with non-proportional thinking. Further, lower-priced stocks also experience weaker post earnings announcement drift.

Finally, we show that non-proportional thinking is an important determinant of return reversals. If investors overreact to news for lower-priced stocks, then we would expect these stocks to experience stronger subsequent reversals as prices return to fundamentals. Consistent with non-proportional thinking, we find that both the long-run reversal anomaly documented by De Bondt and Thaler (1985) and the short-run reversal anomaly documented by Jegadeesh (1990) are stronger for lower-priced stocks. Further, the magnitude of return reversals can be better sorted by price than by size.

Our non-proportional thinking hypothesis is motivated by related findings in the psychology literature documenting a well-known bias sometimes described as "denominator neglect" or "ratio bias," which is the tendency of individuals to focus excessively on numerators when comparing ratios. For example, people have been shown to perceive 10 out of 100 as being larger than 1 out of 10. Miller, Turnbull, and McFarland (1989) was the first to document this phenomenon and it has since been replicated in many different contexts (see, e.g., Kirkpatrick and Epstein, 1992; Denes-Raj and Epstein, 1994; Pacini and Epstein, 1999). One application that has received much attention is the reporting of health risks. For example, Yamagishi (1997) finds that cancer is perceived as riskier when described as killing 1,286 out of 10,000 people (12.86%) than when described as killing 24.14 out of 100 people (24.14%).[2] Kirkpatrick and Epstein (1992) hypothesize that denominator neglect results from individuals processing information through two partially independent systems—a rational system that operates according to a person's understanding of conventionally established rules of logic and evidence, and an experiential system that processes information automatically and more simply. Interestingly, Denes-Raj and Epstein (1994) show that this bias persists even when individuals are explicitly presented with ratios in decimal format alongside the fractional representations.

In our paper, we are interested in a stock's return response to news, which is a ratio—the numerator being the dollar change in the stock's price, and the denominator being the stock's price prior to the news. Non-proportional thinking implies that people focus on dollar reactions to news and underattend to the denominator. This would lead individuals to perceive the same return response as being smaller for a low-priced stock than for a high-priced stock. Equivalently, a low-priced stock would need to have a larger *true* return response in order to have the same *perceived* return response as a high-priced stock. Consistent with this idea, Svedsäter, Gamble, and Gärling (2007) show in a lab setting that non-proportional thinking influences how individuals translate news into beliefs about stock prices. Specifically, they find that, following the same earnings news, experimental participants anticipate a larger return response for low-priced stocks than for high-priced stocks. Our findings suggest that these experimental results, based on undergraduate participants, actually generalize to real financial markets.[3]

Our results contribute to the finance literature by shedding new light on how news is impounded into stock prices. Much of the literature on news processing has focused on investor inattention (e.g.,

[2]See also, Trope and Liberman (2003), Pinto-Prades, Martinez-Perez, and Abellán-Perpiñán (2006), Bonner and Newell (2008).

[3]Our findings are also related to a separate "relative thinking" phenomenon, where people have been shown to overattend to denominators in situations in which a denominator should not be used in the first place (e.g., Thaler, 1980; Pratt, Wise, and Zeckhauser, 1979; Azar, 2007; Bushong, Rabin, and Schwartzstein, 2015; and Lian, Ma, and Wang (2018). Specifically, in comparing two integers, individuals seem to scale the difference between them by a level, even when the raw difference is all that is relevant. For example, individuals are more willing to travel 20 minutes to save $5 on a $15 calculator than to save $5 on a $125 calculator (Tversky and Kahneman, 1981). Non-proportional thinking and relative thinking are not necessarily inconsistent with one another. People may both underattend to denominators when they should fully take them into account, but also overattend to denominators when they should fully ignore them. In other words, the two phenomena are defined relative to different rational benchmarks. In the case of stock returns, the rational benchmark calls for denominators to be fully taken into account; therefore, non-proportional thinking is the more relevant bias.

Hirshleifer and Teoh, 2003; Barber and Odean, 2008; Giglio and Shue, 2014), in which investors fail to attend to various forms of value-relevant news. In contrast, our paper suggests that, even when investors do attend to news, non-proportional thinking leads them to consistently translate that news into stock price impacts in a biased way.

Our findings also document a new way in which thinking about changes in value in the wrong units can affect financial markets. In related work, Shue and Townsend (2017) show that the tendency to think about executive option grants in terms of the *number* of options granted rather than the Black-Scholes value contributed to the dramatic rise in CEO pay starting in the late 1990s. Birru and Wang (2015, 2016) show that nominal price illusion causes investors to mistakenly believe that lower-priced stocks have more "room to grow." Roger, Roger, and Schatt (2018) show that sell-side analysts issue more extreme forecasts for lower-priced stocks.[4] Finally, our research is related to Baker and Wurgler (2004a,b), Baker, Nagel, and Wurgler (2007), and Hartzmark and Solomon (2017, 2018), which show that investors fail to incorporate dividends when evaluating total returns.[5]

Further adding to our contribution, we show that non-proportional thinking can help to explain a variety of widely-cited asset pricing phenomena. As discussed earlier, we show that the well-known size-volatility and size-beta relations are actually driven by the correlation between size and price. This fact calls into question the notion that size is a fundamental determinant of risk. In addition, we show that the leverage effect is largely driven by the correlation between past returns and price. Finally, we show non-proportional thinking can contribute to over- and underreaction to news and subsequent reversal/drift patterns in asset prices. In particular, post-earnings announcement drift is stronger among higher-priced stocks, which also exhibit lower initial responses to earnings news. At the same time, short and long-term reversals are stronger among lower-priced stocks, which also respond more strongly to news in general.

Finally, we note that some of the basic empirical facts collected in this paper have been individ-

[4]Roger, Roger, and Schatt (2018) interpret their results as consistent with analysts thinking about small numbers in a linear scale and large numbers in a logarithmic scale. However, we believe their evidence may also be consistent with non-proportional thinking in which analysts make predictions for dollar changes in earnings per share, without fully scaling by share price.

[5]Our research is similar in spirit to the money illusion literature, which shows that households confuse the nominal and real value of money (e.g., Fisher, 1928; Benartzi and Thaler, 1995; Modigliani and Cohn, 1979; Ritter and Warr, 2002). In this paper, we show that investors focus on dollar units instead of percentage units. Our research is also related to the broader literature on behavioral finance, particularly Lamont and Thaler (2003), which asks whether investors can "add and subtract," and is the inspiration for the title of this paper.

ually shown in previous research. However, the previous literature has often presented these facts as puzzles. For example, an increase in volatility following splits was discussed in early work by Ohlson and Penman (1985), and the general negative relation between price and volatility is well-known in the asset pricing literature (e.g., Black, 1976). However, unlike prior work, we begin with the hypothesis of non-proportional thinking in mind. This allows us to present a more targeted set of empirical tests, across a variety of settings, to distinguish non-proportional thinking from other potential explanations. As far as we are aware, this paper is the first to seriously examine the possibility of non-proportional thinking in real financial markets.

2 Empirical Framework

Consider a stock with current share price P, just before news is released. Suppose news Z is released that contains information relevant for the valuation of the stock. We assume that if markets are fully efficient and rational, the release of news Z should imply a δ percentage change in the price of the stock. In other words, δ is the rational return response to the news. However, non-proportional thinking may lead investors to apply a heuristic and think that news Z should move prices by a dollar amount X. In this case, the return response to news would be $\frac{X}{P}$ rather than δ. A return response of $\frac{X}{P}$ would represent the most extreme form of non-proportional thinking. However, investors may only engage in partial non-proportional thinking. To capture this, we consider a return response function that nests proportional and non-proportional thinking:

$$r = \delta \left(\frac{\eta_0}{P}\right)^{\theta}, \tag{1}$$

where the parameter η_0 is a constant equal to $\frac{X}{\delta}$ and the parameter $\theta \in [0, 1]$ captures the extent to which investors engage in non-proportional thinking. When $\theta = 0$, investors are fully rational and the return response is $r = \delta$. When $\theta = 1$, the return response is $r = \frac{X}{P}$. In the presence of non-proportional thinking ($0 < \theta \leq 1$), Equation 1 implies that the magnitude of the return response to news, $|r|$, will be greater, the lower the stock's price, P. One interpretation of η_0 is as the price level such that the dollar response X corresponds to the rational return response δ, even when investors engage fully in non-proportional thinking (i.e., $\theta = 1$).

To move closer to an estimating equation, Equation 1 can also be expressed linearly by taking logs:

$$log\left(|r|\right) = log\left(|\delta|\right) + \theta log\left(\eta_0\right) - \theta log\left(P\right). \tag{2}$$

Of course, we cannot typically observe δ and η_0 in the data. However, to the extent that they are orthogonal to P, we can still estimate θ from Equation 2, omitting these variables. Given that nominal share prices are fairly arbitrary, it may be plausible that P would be orthogonal to δ and η_0, especially after conditioning on other observable stock characteristics (e.g., size), or by comparing the same stock immediately before and after a stock split. In some tests, we also explicitly control for the magnitude of the news shock or restrict to a sample of S&P 500 firms for which is it more plausible that δ is orthogonal to P.[6]

This framework also delivers predictions for a stock's return volatility. If we allow for a sequence of *iid* news arriving over time corresponding to volatility σ_δ, Equation 1 implies that:

$$\sigma_r = \sigma_\delta \cdot \left(\frac{\eta_0}{P}\right)^\theta. \tag{3}$$

In the presence of non-proportional thinking ($0 < \theta \leq 1$), this means that a stock's volatility will be greater, the lower the stock's price. This can be also be expressed in log form as:

$$log\left(\sigma_r\right) = log\left(\sigma_\delta\right) + \theta log\left(\eta_0\right) - \theta log\left(P\right). \tag{4}$$

The prediction that lower-priced stocks should have higher volatility applies to different measures of volatility, including total return volatility, idiosyncratic volatility, and absolute market beta. Lower-priced stocks would have higher idiosyncratic volatility due to their greater responsiveness to firm-specific news. They would also have higher absolute market beta due to their greater responsiveness to aggregate news. Note that non-proportional thinking amplifies the *absolute value* of market beta. For example, if a stock's true beta is negative and aggregate news is positive, the

[6]We also acknowledge that assuming that δ and η_0 are orthogonal to P may be an oversimplification of a more complex model that actually drives investor behavior. Nevertheless, we show in Figure 2, Panel B, that a model with these assumptions fits the data reasonably well.

stock's share price should drop and the share price should drop by more if investors overreact to the news. Together, greater idiosyncratic volatility and absolute market beta would lead to greater total volatility.

These predictions apply broadly to all types of news that move stock prices. This includes news about cash flows as well as news about discount rates (e.g., a shock to risk-aversion); it also includes firm-specific news as well as news that is aggregate in nature.[7] It could even include uninformative news that some investors mistakenly believe to be informative—what Shleifer and Summers (1990) call "pseudo-signals."

Because news events are difficult to observe systematically, we begin our analysis of non-proportional thinking by testing our predictions for the relation between nominal price and return volatility, estimating variants of Equation 4. We then use several approaches to identify news events. Using these identified news events, we test our predictions about the relation between nominal price and return responses to news, estimating variants of Equation 2.

3 Data

The sample period for our baseline analysis runs from 1926–2016. However, the beginning of the sample period for each empirical test varies depending on when coverage begins for supplementary data sources used in the analysis. We show that our results are robust across different time periods.

Summary statistics for our key variables can be found in Table 1 Panel A. A suggestive preview of our main findings can be seen in Panel B, which reports the correlations between our main variables of interest. We find a strong negative correlation of -0.578 between volatility and lagged price. The absolute magnitude of the correlation between price and volatility is much stronger than the correlations between volatility and proxies for trading frictions such as size, volume turnover, and bid-ask spread, which take on the values of -0.329, 0.168, and 0.120 respectively.

[7] For example, investors should lower their valuation of risky stocks if they experience a shock to their risk aversion. In the extreme, non-proportional thinking may lead newly risk-averse investors to lower the value of differently-priced stocks (that are otherwise similar) by the same dollar amount, leading to a larger return drop for lower-priced stocks.

Stock Market Data

We obtain stock market data from CRSP, which contains information relating to returns, nominal share prices, stock splits, daily high and low, volume, bid-ask spread, and market capitalization. Data on factor returns and size category cutoffs come from the Ken French Data Library. We restrict the sample to stocks that are publicly traded on the NYSE, American Stock Exchange, or NASDAQ. We also restrict the sample to assets that are classified as common equity (CRSP share codes 10 and 11).

In our baseline tests, we measure stock i's total return volatility in month t as the annualized standard deviation of its daily returns within that month. We measure stock i's market beta in month t by regressing its daily excess returns within that month on market excess returns. Because non-synchronous prices have been shown to have a big impact on short-horizon betas, we follow Dimson (1979) and include both current and lagged market excess returns in the regressions, estimating beta as the sum of the slopes on all lags. Specifically, we include four lags of market returns, imposing the constraint that lags 2–4 have the same slope to reduce the number of parameters, as in Lewellen and Nagel (2006). We measure idiosyncratic volatility as the annualized standard deviation of the residuals from these regressions.

To classify stocks by nominal share price, past returns, etc., we always use lagged information to avoid look-ahead bias. To reduce the influence of outliers, we restrict our baseline analysis to stock-months where (1) there are at least 15 trading days with non-missing return data in CRSP and (2) there is variation in the stock's price (i.e., the stock price is not the same on all trading days within the month) and (3) the nominal stock price at the end of the previous month was not in the top or bottom 1% of stock prices that month.

Firm Accounting Data

We use accounting data to control for firm characteristics. These data come from the COMPUSTAT Quarterly Fundamentals file. Coverage begins in 1961. The primary control variables we construct are sales volatility, market-to-book ratio, and leverage. We define sales volatility as the standard deviation of year-over-year quarterly sales growth during the previous four quarters.[8] In cases where data are missing for some of the previous four quarters, we compute the standard deviation based on the non-missing quarters, conditional on there being more than one non-missing quarter. We define the market-to-book ratio as market capitalization (csho*prcc_f) plus the book value of assets (at) less shareholder equity (seq), all divided by the book value of assets (at). We define leverage as the ratio of short-term and long-term debt (dlc+dltt) to the book value of assets (at).

Institutional and Retail Ownership

Data on institutional ownership and mutual fund ownership come from 13f filings as captured by the Thomson Financial S34 and S12 databases, respectively. Coverage begins in 1980. To measure institutional ownership percentages each quarter, we sum up the number of shares of each stock held by 13f filers and divide by the number of shares outstanding. Data on the characteristics of a firm's retail shareholders come from Odean's (1998) "Large Discount Broker" database.

News Events

To identify news events, we use data from Boudoukh et al. (2018), which identifies value-relevant events by applying a machine learning algorithm to the text of articles from *Dow Jones Newswire*. News events are divided into two groups: events that the algorithm can place into a particular category and events that it is unable to categorize. The Boudoukh et al. (2018) data are limited to S&P 500 stocks, with coverage beginning in 2000.

Earnings Announcements

Data on quarterly earnings announcements come from the I/B/E/S detail file. Coverage begins in 1983. These data provide information on analyst forecasts of earnings per share, along with the actual announced earnings per share. Following the literature (e.g., Mendenhall 2004; Jegadeesh

[8] For each quarter, we compute the growth of sales (sale) over the year-ago quarter. We consider year-over-year sales growth to be undefined if sales are reported to be negative in one of the two quarters.

and Livnat 2006), we define standardized unexpected earnings (SUE) as:

$$SUE_{i,t} = \frac{(AE_{i,t} - FE_{i,t})}{\sigma_{i,t}} \tag{5}$$

where for firm i in quarter t, $AE_{i,t}$ represents the actual earnings, $FE_{i,t}$ represents mean forecasted earnings, and σ_{it} represents the standard deviation of analyst forecasts. Thus, $SUE_{i,t}$ is a measure of how surprising an earnings announcement was, given the distribution of analyst forecasts. It is only defined for earnings announcements with multiple forecasts. We compute the variables $FE_{i,t}$ and $\sigma_{i,t}$ using only the most recent forecast of each analyst prior to the earning announcement. To avoid using stale information in our measure of analyst expectations, we exclude forecasts that are made more than 60 days prior to the announcement. Our results remain similar if we exclude forecasts made more than 30 days prior to the announcement.

4 Results: Volatility

4.1 Prices, Total Volatility, Idiosyncratic Volatility, and Market Beta

We begin by exploring how return volatility varies with share price. Following the empirical framework laid out in Section 2, we estimate equations of the form:

$$log\,(vol_{i,t}) = \beta_0 + \beta_1 log\,(price_{i,t-1}) + controls + \tau_t + \epsilon_{it}, \tag{6}$$

where $vol_{i,t}$ represents stock i's volatility in month t, $price_{i,t-1}$ represents the stock's nominal share price at the end of the previous month, τ_t represents calendar-year-month fixed effects, and $controls$ represents additional control variables. Volatility can mean total volatility, idiosyncratic volatility, or market beta. Control variables can include the log of the firm's size (measured as total market equity) in the previous month or indicator variables for 20 size categories based on the market capitalization of the stock relative to the size breakpoints for each year-month from the Ken French Data Library. The sample excludes observations with extreme lagged prices (the bottom and top 1% of prices each month). To account for correlated observations, we double-cluster standard errors by stock and year-month.

We present our baseline results in Table 2. Consistent with non-proportional thinking, we find that higher nominal share price is associated with lower total return volatility. The negative coefficient on price remains highly significant and stable in magnitude as we introduce control variables for size (either as the log of lagged market capitalization or with 20 size category indicators based on lagged market capitalization). The results hold in the cross section (with time fixed effects and without stock fixed effects) and in the time-series (with both time and stock fixed effects), as shown in Panels A and B, respectively. The economic magnitudes are also quite large. With the full set of control variables in column (4), a doubling in share price is associated with a 34% decline in volatility in the cross section and a 27% decline in volatility in the time-series (i.e., within stock over time). While our empirical framework is not intended to offer an exact model for the data, we can interpret these coefficient estimates as implying that θ in Equation 4 is approximately 0.3. In other words, investors display an intermediate level of non-proportional thinking.

In Table 3, we find similar empirical patterns after replacing the dependent variable with idiosyncratic volatility and market beta. The economic magnitudes are again large. With the full set of control variables in column (4), a doubling in share price is associated with a 35% decline in idiosyncratic volatility and a 31% decline in market beta. As discussed previously, we use the absolute value of market beta as our dependent variable because non-proportional thinking should lead to stronger reactions to market news for lower-priced stocks, resulting in more positive betas for positive-beta stocks and more negative betas for negative-beta stocks. However, one may be concerned that stocks with measured betas in the negative range may simply be stocks where beta is measured with error. To show that this does not drive our results, Appendix Table A1 restricts the sample to observations with positive estimated market betas. We continue to find similar results in this subsample.

In Figure 2, we explore the shape of the price-volatility relation, without imposing a linear log-log structure. In Panel A, we plot the coefficients of a regression of volatility on 20 lagged share price bin indicators, with each bin containing the same number of observations, controlling for 20 size category bins and year-month fixed effects. All plotted coefficients measure the difference in volatility within each share price bin relative to the omitted bin of 20 (the largest share price). In Panel B, we plot the coefficients of a regression of volatility on 20 lagged share price bin indicators, this time with each bin representing an equal range of logged prices, again controlling for size and time fixed effects. The omitted category represents log lagged share price in the range of 5.0 to 5.25. In both flexible specifications, we observe a strong monotonic negative relation between volatility and share price. These figures show that our findings of a negative relation between volatility and nominal share price are unlikely to be driven by a few outlier observations. Rather, the negative relation holds between any two adjacent nominal price bins, and holds even in the range of high nominal share prices. Panel B also shows that the relation between the logarithm of volatility and the logarithm of share price is approximately linear, with a slight decrease in the absolute slope for very high-priced stocks. Thus, Panel B supports our use of a simple log-linear model as a reasonable way to represent the data in a parsimonious manner.

Our baseline analysis uses panel data at the stock-year-month level and exploits both cross-sectional and time-series variation. To show that our findings are not caused by biases in the potential misspecification of time series or panel regressions, we can alternatively estimate the pure cross-sectional relation between volatility and lagged price within each month in our sample, i.e., a Fama-MacBeth-style analysis. We estimate Equation 6, controlling for size category fixed effects, separately for each of the 1085 calendar year-months in our sample. Figure 3 plots the histogram of β_1, as estimated from 1085 cross-sectional regressions. The mean of the estimated coefficients is -0.31, with a standard deviation of 0.10, and almost all estimates are negative. Thus, we find a similarly-sized and robust negative volatility-price relation using only cross-sectional variation.

4.1.1 Size Doesn't Matter (Much)

The empirical patterns shown so far are consistent with non-proportional thinking. However, an omitted factor could determine both price and volatility. Our results can already reject one key alternative explanation involving size: It is well-known in the asset pricing literature that small-cap stocks (i.e., stocks with low market capitalization) tend to have higher return volatility, idiosyncratic volatility, and market beta. Since small-cap stocks also tend to have low nominal share prices (see

Table 1 for correlations), size may simultaneously determine share price and volatility.

However, we showed in Tables 2 and 3 that the coefficient on lagged share price remains stable in magnitude and significant after controlling for the logarithm of lagged market capitalization or after controlling flexibly for size with 20 size category indicators. We also see in columns (2) and (3) of each table that, while size negatively predicts volatility if we do not control for price, the size-volatility relation flattens toward zero once we control for lagged nominal share price.

As an alternative way of illustrating these results, we note that size is equal to the product of price and shares outstanding. Therefore, we can examine whether the negative volatility-size relation is driven by price or shares outstanding, by regressing volatility on lagged price and lagged shares. Appendix Table A2 shows that the negative volatility-size relation is driven by price rather than shares outstanding.

We explore the relation between size and volatility in more detail in Figure 4. Panel A shows the coefficients from a regression of log total volatility (left) or log market beta (right) on 20 size category indicators (the largest size category is the omitted one), after controlling for year-month fixed effects. As expected, we find a strong negative relation between size and volatility and a strong negative relation between size and beta. In Panel B, we report the same set of coefficients for the 20 size indicators, after adding a single control variable for the log of the lagged nominal share price to the regression. We see that the relation between size and volatility, and size and beta, flattens dramatically. In the range between size categories 4 and 20, size continues to negatively predict volatility and beta. However, the magnitude of the slope shrinks by more than 80 percent.[9] These results cast doubt on the notion that size is a fundamental determinant of risk, as measured by volatility or market beta. Rather, a significant portion of the well-known size-volatility and size-beta empirical relations is driven by share price, in a manner consistent with non-proportional thinking.

[9]In the range of size categories 1 through 4, the relation between beta and size is positive after controlling for price. However, beta may be measured with more error for these micro-cap stocks.

4.1.2 The Leverage Effect Puzzle

A large body of research in asset pricing has explored the leverage effect puzzle, which refers to the strong negative relation between volatility and past returns in stock market data (e.g., Black, 1976). The phenomenon is named after a potential explanation involving leverage: holding debt levels constant, negative returns imply that the equity is more levered, leading to increased equity volatility (e.g., Christie, 1982). However, some have pointed out that the leverage-based explanation may be incomplete because the negative volatility-return relation is equally strong for firms with zero book leverage (e.g., Hasanhodzic and Lo, 2011), and others have offered non-leverage-based explanations (e.g., Campbell and Hentschel, 1992).

In this paper, we do not seek to reject any of the existing explanations of the leverage effect puzzle. Instead, we propose non-proportional thinking as a new and potentially complementary explanation. Negative past returns imply a drop in share price, and a lower share price causes an increase in volatility if investors engage in non-proportional thinking.

In Table 4, Panel A, we present regressions of volatility in the current month on past returns and share price, controlling for firm size categories and year-month fixed effects. First, in column (1) we repeat our baseline specification, limiting the sample to stock-year-months where returns over the previous 12 months are non-missing. In column (2), we replace lagged price with returns over the previous 12 months. We find that volatility is indeed strongly negatively related to past returns, with a coefficient of -0.24 on the measure of past returns. However, when we add a control for the lagged share price at the end of the previous month in column (3), the coefficient on past returns falls in absolute magnitude to -0.03. Further, the coefficient on lagged price (after controlling for past returns) remains stable in magnitude at approximately -0.33. In other words, the coefficient on past returns falls by 87% in absolute magnitude once we add an additional control variable for price. Conversely, the coefficient on lagged price falls by a negligible 2% once we add a control variable for past returns. These results show that a large portion of the negative volatility-return relation may actually be driven by the correlation between past returns and share price. We also find similar patterns if we control for past returns separately for each the previous 12 months as in column (4). Altogether, these results show that, while price is correlated with past returns (see

Table 1 for correlations), the price level is a stronger determinant of volatility. Controlling for the price level, it matters less how the stock arrived at that level, either through negative past returns or positive past returns.

One may still be concerned that our findings are driven by a negative relation between price and leverage, and a positive effect of leverage on equity volatility. To further rule out this possibility, in Table 4, Panel B, we limit the sample to stocks associated with firms with zero debt (current liabilities + long term debt) reported in their most recent quarterly financial statements. We continue to find similar results in this subsample.[10]

4.1.3 Robustness and Heterogeneity

Thus far, we have shown evidence that the price-volatility relation is not driven by size. However, it remains possible that lower-priced stocks tend to be more volatile because they are associated with higher microstructure frictions. In this section, we show that the price-volatility relation also remains stable after controlling for a host of additional firm/stock characteristics beyond size. The robustness of our estimates to these controls either suggests that microstructure frictions do not play a major role driving the price-volatility relation, or that price is much more closely related to microstructure frictions than commonly-used measures such as size, volume, and bid-ask spread. While we acknowledge that we cannot completely rule out the latter possibility, we do not think that it constitutes a likely explanation for our findings.

Additional Controls

In Table 5, we repeat our baseline analysis including additional control variables that could affect volatility. In column (1), we begin by including minimal controls, as in column (1) of Table 2 Panel A. In column (2), we control for size more flexibly than before by controlling for both the logarithm of lagged market capitalization as well as the 20 size category indicator variables and all interactions between the two. Using these flexible size controls, we continue to estimate a similar coefficient on price. In column (3), we add an additional control for lagged sales volatility, which

[10]We acknowledge that firms with zero debt may still have operating leverage, which may increase the risk of equity. It is not the goal of this paper to show that leverage cannot contribute to a leverage effect. Rather, we argue that a substantial portion of the leverage effect can be explained by non-proportional thinking.

is a proxy for the fundamental volatility of each firm. This is measured as the standard deviation of year-over-year quarterly sales growth in the four most recently completed quarters. In column (4), we include a control for the stock's market-to-book ratio. In column (5) we control for volume turnover ($\frac{Share\,Volume}{Shares\,Outstanding}$) and bid-ask spread percentage ($100 \times \frac{Ask-Bid}{Ask}$). In column (6), we control for leverage ($\frac{Current\,Liabilities+Long\,Term\,Debt}{Book\,Assets}$). In all columns, we only include observations where all controls are non-missing so as to keep the sample consistent. While we estimate significant coefficients on many of these control variables, suggesting that they are indeed related to volatility, their inclusion has little effect on the estimated price coefficient. Therefore, our results do not, for example, appear to be driven by lower-priced stocks having higher fundamental sales volatility or lower liquidity.

In Appendix Table A3, we also control for size even more thoroughly and flexibly by controlling for up to 500 size category indicators, each interacted with the logarithm of lagged market capitalization. This specification allows volatility to vary with a 500-part spline in size, and allows for discontinuous jumps with size coinciding with each of the 499 inflection points. The results remain similar controlling for size in this way.

Tick Size

A tick is the minimum unit for the price movement of a financial security. Tick size as a fraction of share price is larger for stocks with lower nominal share price, which may artificially inflate the measured volatility of lower-priced stocks.

In Figure 2, described previously, we found that the negative price-volatility relation holds even in the range of very high nominal share price bins, where tick size limits should have minimal impact. We will also show in Appendix Table A4 that the absolute magnitude of the price-volatility relation does not display a downward trend over time, even though tick sizes have fallen dramatically in recent decades.[11]

To further ensure that our results are not driven by tick sizes being large relative to prices for lower-priced stocks, in Table 6, we check that our results are robust to linear measures of

[11]Tick sizes moved from 1/8 to 1/16 in 1997 and from 1/16 to 0.01 in 2001.

volatility, which have been shown to be insensitive to tick sizes (Hau, 2006). Intuitively, with linear measures, rounding errors leading to artificially large price movements are canceled out by rounding errors leading to artificially small price movements on average. We find similar results when using such linear measures. Specifically, we measure volatility as (1) the mean intraday price range percentage ($100 \times \frac{High-Low}{High}$) over all trading days in a stock-month, (2) the mean absolute deviation ($|Ret - \overline{Ret}|$) over all trading days in stock-month, and (3) the mean absolute return ($|Ret|$) over all trading days in a stock-month. We continue to estimate similar coefficients using these three measures of volatility. Therefore, our results do not appear to be driven by tick sizes being large relative to stock prices for low-priced stocks.

Institutional Ownership

Institutional investors may be more sophisticated than non-institutional investors and thus less likely to suffer from non-proportional thinking. If so, the price-volatility relation should be weaker for stocks with higher institutional ownership. To test whether this is the case, we repeat our baseline analysis, allowing the effect of price to interact with institutional ownership.[12] The results are shown in Table 7. Consistent with the idea that institutional investors are more sophisticated, we estimate that volatility declines with price less when a stock has higher institutional ownership. A linear extrapolation implies that, as a stock moves from 0% institutional ownership to 100%, the effect of price on volatility is reduced by approximately 44%.

This analysis also partially addresses another potential alternative explanation, which is that lower-priced stocks may be held by unsophisticated noise traders or speculators who generate high volatility for reasons unrelated to non-proportional thinking. Table 7 shows that, indeed, stocks are more volatile when held by more unsophisticated investors. However, even among stocks with the same institutional ownership, lower-priced stocks are still more volatile.

[12] As is standard in the literature, we define institutional ownership as the percent of outstanding shares reported to be held by institutions in quarterly 13f filings. The institutional ownership variable is updated quarterly, while our observations are at the monthly level. As before, we double-cluster standard errors by stock as well as year-month. The stock clustering should address the mechanical serial correlation in institutional ownership induced by the quarterly updating (as well as any other source of serial correlation in the error term of a given stock over time).

Size Subsamples

While we have controlled for size to ensure that the estimated relation between price and volatility is not actually a size-volatility relation, we have not examined how the price-volatility relation varies with size. In Appendix Table A5, we repeat our baseline analysis in each of 20 size categories. As before, these size category bins come from Ken French's ME Breakpoints file. The breakpoints for a given month are based on the size distribution of stocks traded on the New York Stock Exchange in that month, with a breakpoint for every fifth percentile. Because our sample includes all stocks traded on the NYSE, AMEX, and NASDAQ exchanges, observations in our data are not equally distributed across the size categories.

As can be seen, our main finding is not a "micro-cap phenomenon" or even a "small-cap phenomenon." The negative relation between price and volatility continues to hold even among stocks in the top 5th percentile of the NYSE size distribution. Not surprisingly though, the magnitude of the volatility-price relation does decline with size, consistent with mispricing being less prevalent for large-cap stocks, which may suffer less from limits to arbitrage.

Time Period Subsamples

In Appendix Table A4, we explore how the price-volatility relation has changed over time by repeating our baseline analysis in separate subsamples for each decade from the 1920s to the end of our sample period in 2016. We find that the coefficient is relatively stable across these different time periods and there are no secular trends. Thus, it does not seem that the relation has disappeared in recent years or is weakening over time. This also serves as additional evidence that tick size limitations do not drive our results, because tick sizes have declined over time.

Upside and Downside Volatility

Non-proportional thinking predicts that higher share price leads to less extreme return responses to both positive and negative news. In Appendix Table A6, we show that share price is negatively related to both upside and downside volatility. Therefore, our results cannot be explained by other factors or anomalies that only affect one tail of returns. We measure upside (downside) volatility as the log of mean daily squared returns in each month conditional on the returns being positive (negative). We find that a doubling in share prices is associated with a greater than 30% decline in both upside and downside volatility. We can also measure upside (downside) market beta as the beta estimated using only days when the market return is positive (negative). We find that a doubling in share prices is associated with a greater than 30% decline in both upside and downside beta.

4.2 Stock Splits

Although we have controlled for many observable factors that could affect volatility, it remains possible that omitted variables may drive the negative relation between price and volatility. To better account for potential omitted factors, we study periods immediately surrounding stock splits. For standard 2-for-1 stock splits, the share price falls by 50%. Non-proportional thinking predicts an immediate and persistent increase in volatility after the pre-announced split execution date. While stock splits are not completely randomly assigned across firms, the fundamentals of each firm are unlikely to change exactly on pre-announced stock split execution dates.[13] Therefore, we can credibly attribute changes in volatility immediately after the split execution date to the change in share price.

4.2.1 Daily Analysis

We begin with granular daily stock return data to estimate a regression discontinuity around the date of the stock split. For the regression discontinuity, we change our measure of volatility from the standard deviation of daily returns within each calendar month to the intraday price range percentage ($100 \times \frac{High-Low}{High}$).[14] We omit the actual day of the split from the analysis, as it is not clear whether the split takes place at the beginning of the trading day or the end. We begin by considering only 2-for-1 stock splits, in which one old share is converted to two new shares, as this is the most common type of split in the data.

[13]For a discussion of factors that may affect split decisions, see Weld et al. (2009) and Baker, Greenwood, and Wurgler (2009).

[14]In principle, one could also use intraday trading data from TAQ to address this question, but those data are only available for more recent years, and we see no reason that using such data would lead to different conclusions.

In Figure 5, we non-parametrically estimate the intraday price range percentage in the 45 days before and after a split using local linear regression (with a triangular kernel and rule-of-thumb optimal bandwidth).[15] We find that the intraday price range percentage increases by 1.4 immediately after the split. The jump in intraday price range percentage persists with a small decay over the next 45 trading days. Corresponding regression results are shown in Appendix Table A7. The magnitudes are very similar regardless of the kernel or bandwidth used.

One concern may be that the increase in volatility following a split almost seems too fast to be consistent with non-proportional thinking. Specifically, one may worry that it is unlikely that there would happen to be major news about stocks the day after splits. However, our regression discontinuity test does not require this to be the case. A stock's volatility should (at least partly) reflect the flow of news investors believe to be relevant for each stock, even if that flow of news does not usually contain major events. For the same news process before and after a split, non-proportional thinking predicts a persistent and immediate jump in volatility after the split, because investors react to the same news process in dollar units, translating into larger absolute return movements after the split. We also note that the type of "news" relevant for non-proportional thinking is very broad, as it essentially includes any type of news that moves stock prices. Non-proportional thinking would lead lower-priced stocks to respond more strongly in percentage terms to both news about cash flows and news about discount rates, as well as to both firm-specific news and aggregate market/macro news (which arguably is released at a high frequency). Non-proportional thinking would even lead lower-priced stocks to respond more strongly to non-informative news that some investors wrongly believe to be informative—what Shleifer and Summers (1990) call "pseudo-signals." Given the broad type of news that is relevant for our hypothesis, this news likely occurs at a high enough frequency to lead to increased volatility immediately after a split. Moreover, our interpretation of Figure 5 does not require that every stock experiences news immediately after a split—it only requires that some do.

[15] We limit the sample to splits that are neither preceded by another split (for the same stock) in the previous 90 days, nor followed by another split in the subsequent 90 days, so that our estimation windows do not overlap with other splits.

4.2.2 Monthly Analysis

We also conduct event studies examining changes in total volatility, idiosyncratic volatility, and market beta around stock splits using monthly data. To explore how these measures of volatility change after splits, we estimate the following regression:

$$log\,(vol_{i,t}) = \alpha + \sum_{k=-6}^{6} \beta_k \mathbb{1}(EventMonth_{i,t} = k) + \tau_t + \nu_i + \epsilon_{i,t}, \tag{7}$$

where $\mathbb{1}(EventMonth_{i,t} = k)$ are indicator variables equal to one if month t is k months before or after a split month for stock i, τ_t are calendar year-month fixed effects, and ν_i are stock fixed effects. Observations are at the stock-month level, and the sample is limited to the six months before and after a split. The coefficients β_k measure the difference in volatility in event month k relative to month $t-1$, the omitted category.[16] We show results for 2-for-1 splits alongside those for 3-for-2 splits to facilitate comparisons. In a 2-for-1 split, one share is converted into two shares, such that the price drops by 50%. In a 3-for-2 split, two shares are converted into three shares, such that the price drops by 33%. By comparing these two types of splits, we can control for common factors that might accompany both types of positive splits, while isolating a causal effect of the additional drop in price associated with 2-for-1 splits.

We find that total volatility, idiosyncratic volatility, and market beta rise significantly after stock splits. These patterns are shown graphically in Figure 6, which plots the β_k coefficients from equation 7. We exclude the split month from these figures, as split months contain both pre-split and post-split days. As can be seen, around both 2-for-1 and 3-for-2 splits, we find a sudden large and persistent increase in volatility. In addition, as we would expect, the increase in volatility is significantly larger following 2-for-1 splits (where nominal prices drop by 50%) than following 3-for-2 splits (where nominal prices drop by 33%).

In terms of magnitudes, our analysis of changes in volatility following splits yields estimates that are remarkably consistent with those from the cross-sectional regressions presented in Section

[16] We limit the sample to splits that are neither preceded by another split (for the same stock) in the previous 12 months, nor followed by another split in the subsequent 12 months, so that our estimation windows do not overlap with other splits.

4.1. In Table 2, we estimated that $\theta \approx 0.34$, i.e., a one unit change in log price corresponds to a 0.34 unit change in log volatility. In Figure 6, for a 2-for-1 split in which the price is divided by 2 (equivalent to a decline of 0.7 log points), we observe a 0.25 unit change in log volatility, implying that $\theta \approx 0.35$. For a 3-for-2 split in which price is divided by 1.5 (equivalent to a decline of 0.4 log points), we observe a 0.15 unit change in log volatility, implying that $\theta \approx 0.37$. The consistency of these estimates of θ across tests supports the view that a common non-proportional thinking bias drives the relation between volatility and price in the cross-section as well as for different types of splits.

We note that in Figure 6, we do see evidence of slight pre- and post-trends, with volatility rising in the six months leading up to a split and falling in the six months after. This is consistent with the view that splits are not entirely random. Firms likely choose to engage in stock splits following periods of good performance, which may coincide with a gradual increase in volatility that subsequently reverts back toward the mean. Given the non-random timing of splits, we use a difference-in-differences approach to more cleanly estimate the causal effect of split-induced price declines on volatility. In particular, similar underlying forces likely lead a firm to do a 2-for-1 split as a 3-for-2 split, but the nominal price of a firm's stock declines more in a 2-for-1 split. Thus, we can difference out the trends around 3-for-2 splits (the control group) from those around 2-for-1 splits (the treatment group) to isolate a nominal price effect. To do this, we estimate equations of the form:

$$\begin{aligned} log\left(Volatility_{it}\right) = &\textstyle\sum_{k=-6}^{6} \gamma_k \mathbb{1}(EventMonth_{it} = k) + \\ &\textstyle\sum_{k=-6}^{6} \beta_k \mathbb{1}(TwoForOneSplit_{it}) \times \mathbb{1}(EventMonth_{it} = k) + \tau_t + \nu_i + \epsilon_{it}, \end{aligned} \tag{8}$$

and plot the β_k coefficients on the interaction terms. As can be seen, differencing out the 3-for-2 splits largely eliminates the upward pre-trends and downward post-trends, leaving more of a clear stair-step pattern. This difference-in-differences analysis at the monthly level, combined with our previous regression discontinuity analysis at the daily level, point towards there being a causal effect of price on volatility.

To further bolster a causal interpretation, we also explore changes in volatility following reverse stock splits, in which the number of shares drops sharply and the share price *increases*. Because reverse splits are relatively uncommon, we pool them all together in this case, regardless of how many shares are converted to one. Non-proportional thinking predicts that volatility will decline following reverse stock splits because the nominal share price increases. Consistent with this prediction, Appendix Figure A1 shows that volatility drops by more than 20 percent in the month following a reverse split and the drop remains persistent over the next 6 months.

Finally, given these sharp patterns, one may wonder about the extent to which option traders anticipate the change in volatility following splits and how quickly they update their beliefs after the split. In the Appendix, we show evidence that option traders do not fully anticipate the change in volatility around splits, and that a simple strategy of going long straddles around split execution dates leads to an average 15 percent return (not annualized) over the subsequent 40 trading days.

4.2.3 Robustness

One potential concern may that the price declines associated with splits also increase microstructure frictions. To address this possibility, Appendix Figure A2 repeats the analysis of Figure 6, controlling for volume turnover and bid-ask spread percentage. The results remain similar with these controls. Appendix Table A8 also shows similar results in table form.

One may also be concerned that the results relating to splits are driven by a handful of small-cap stocks. In Appendix Figures A3 and A4, we show that similar empirical patterns exist in a subsample restricted to large-cap stocks in size categories 11 through 20 according to Ken French's market equity breakpoints.

4.2.4 Addressing Remaining Alternative Explanations

Shift Toward Less Sophisticated Investors

A potential alternative explanation for our results is that splits, and lower share prices in general, attract less sophisticated investors who directly increase volatility (Dhar, Goetzmann, and Zhu, 2004). In addressing this alternative explanation, we begin by noting that it would require that splits lead to a very large increase in trading by unsophisticated investors. Foucault, Sraer, and Thesmar (2011) exploit a natural experiment in France to estimate the effect of retail investor trading activity on volatility. They find that an approximate 50% drop in retail trading activity causes only an 8.3% decline in a stock's volatility.[17] This suggests that it would require considerably more than a 50% increase in retail trading activity after a split to account for the approximate 30% increase in volatility that we find.

To explore the possibility that the increase in volatility after splits is driven by increased trading by unsophisticated investors, we begin by examining trading volume around splits. Increased trading by unsophisticated investors would likely lead to increased volume turnover ($\frac{Share\,Volume}{Shares\,Outstanding}$) following a split. However, in Figure 7, we find no significant effect of split-induced price declines on volume turnover. Specifically, volume turnover exhibits a significant upward trend *preceding* splits (consistent with the view that splits are not entirely exogenous and tend to occur in periods with increasing investor interest) but no increase immediately following splits. In fact, volume turnover actually declines following splits, which could be partly due to mean reversion. However, the decline is similar for both 2-for-1 and 3-for-2 splits. Thus, the difference-in-differences graph, which more cleanly isolates the pure price effect of splits, shows no significant change in volume turnover around splits—unlike for volatility where we find a clear stair-step pattern. At the daily level, we also find no evidence of an increase in volume turnover in Appendix Figure A5. Again, if anything, there appears to be a discontinuous decline in volume turnover following a split rather than an increase.[18]

Using data from Odean (1998) and Barber and Odean (2000), we can also directly examine retail trading activity around splits. In Figure 8, we find a brief discontinuous increase in the number of trades by retail investors following a split, with the bulk of the increase in trading coming from increased buying activity. These results suggest that splits do indeed temporarily draw the attention of retail investors. However, this cannot explain the *sustained* increase in volatility that we document following a split, as the increase in retail trading appears to only last a few days, while the increase

[17]Foucault, Sraer, and Thesmar (2011) estimate that the reform led to an approximate 50% decline in the number of retail trades, and a 20 basis point decline in their measure of volatility (*Volatility2*) relative to a mean of 241 basis points (corresponding to an 8.3% decline).

[18]In this case, the decline appears to be driven by a few high volume days right before splits. When we exclude the 4 days before splits from the analysis, the discontinuity becomes statistically insignificant (p-val=0.846).

in volatility continues for many months. In other words, if retail trading volume explained the increase in volatility, we would expect the changes in retail trading volume from Figure 8 to closely mirror the changes in volatility from Figures 5 and 6, but it that is not what we find.

We also directly check for changes in the nature of a stock's investor base after a split. In Appendix Table A9, we compare institutional ownership before a split (based on the last observed 13f filing leading up to the split) and after a split (based on the first observed 13f filing following the split). We find that institutional ownership declines very slightly (from 47.3% to 46.3%) and the decline is not statistically significant.[19] However, even if the level of institutional ownership does not change around splits, it is possible that the *characteristics* of the investors do change. In Figure 9, we check whether the characteristics of non-institutional investors change, again using data from Odean (1998) and Barber and Odean (2000). We find no significant change in the average annual income of retail investors holding a stock following a split. In Figure 10, we also check whether the characteristics of the institutional investors holding a stock change following a split, using data from 13f filings. In the difference-in-differences figures, we find no significant effect of splits on the size or concentration of mutual funds holding a stock.

Non-Proportional Thinking by Reversal Traders

Finally, one may also wonder whether our results could be driven by a different form of non-proportional thinking on the part of reversal traders or liquidity suppliers. Suppose that noise traders move stock prices around arbitrarily, and others try to profit by trading against these arbitrary price movements. If the reversal traders suffer from non-proportional thinking, they may fail to step in for low-priced stocks, as the price movements for these stocks appear small in dollar terms. This would give noise traders more leeway to induce large percentage price movements for low-priced stocks.

For example, suppose a $10 stock went up 10% (a $1 movement) due to noise trader demand. Reversal traders, thinking non-proportionally, might not notice this small dollar-change in price,

[19] Appendix Table A9 also shows that there is no significant change in sales volatility before a split (based on the last four quarters leading up to the split) and after a split (based on the first four quarters following the split). This suggests that splits are not timed in a way that coincides with fundamental changes in firm volatility.

and therefore not trade against it. In that case, the stock would close up 10%. On the other hand, if noise trader demand drove a $20 stock up 10% (a $2 movement), reversal traders might notice, and therefore trade against this price movement. In that case, the stock might close up only 5%. Thus, consistent with our findings, the $10 stock would be more volatile than the $20 stock in terms of the standard deviation of its daily returns.

However, in the example above, both the $10 and $20 stock would have the same initial return (10%) before reversal traders reacted. Therefore, both the $10 and $20 stock would have the same intraday price range percentage ($100 \times \frac{High-Low}{High}$) and the same intraday extreme absolute return ($100 \times max\{|\frac{High-PrevClose}{PrevClose}|, |\frac{Low-PrevClose}{PrevClose}|\}$). It follows that the $10 stock and the $20 stock should be equally volatile in terms of those measures. In contrast, we find in Figure 5 and Appendix Figure A6 that stock splits cause an immediate and persistent increase in intraday price range percentages and intraday extreme absolute returns. This evidence goes against a "non-proportional thinking by reversal traders" interpretation.[20]

5 Results: Return Responses to News Events

5.1 News Events Identified through Textual Analysis

So far, we have focused on testing the volatility predictions from the framework laid out in Section 2. That framework also predicts that stock returns will be more responsive to news for lower-priced firms. Our previous results showing a large jump in market beta after splits already shows that the returns of lower-priced firms are more responsive to aggregate news. In this section, we directly examine return responses to firm-specific news events.

We begin by analyzing data from Boudoukh et al. (2018), which identifies value-relevant news events for S&P 500 firms by applying a machine learning algorithm to the text of articles from *Dow*

[20] In addition to the evidence here, it is not clear that the reversal trader story would fit with our results on beta and responsiveness to identifiable news events like earnings news (presented in the next section). This would require that reversal traders trade in the opposite direction of aggregate market/macro news or earnings news, but less so for low-priced stocks. While it makes sense that reversal traders would want trade in the opposite direction of those who trade on noise, it is less clear why they would trade in the opposite direction of those who trade on aggregate market/macro news or earnings news. They would only do so if they believed that other traders tend to overreact to such news. At least in the case of earnings news, this seems to contradict other evidence pointing toward underreaction.

Jones Newswire. Using these data, we estimate equations of the form:

$$log\left(\left|CAR_{i,[t-1,t+1]}\right|\right) = \beta_0 + \beta_1 log\left(price_{i,t-2}\right) + controls + \tau_{m(t)} + \epsilon_{i,t}, \tag{9}$$

where $CAR_{i,[t-1,t+1]}$ represents the cumulative abnormal returns for stock i around a news event on date t, $price_{i,t-2}$ represents the stock price immediately prior to the event window, and $\tau_{m(t)}$ represents year-month fixed effects.[21] Note that Equation 9 is analogous to Equation 2, derived from the empirical framework in Section 2.

The results are shown in Table 8. Consistent with non-proportional thinking, we find that cumulative abnormal returns around days with firm-specific news events are significantly more extreme for lower-priced stocks. A doubling in share price is associated with a 20 to 30% decline in the absolute magnitude of the return response. The pattern is similar for news that can be categorized (the first two columns) and for other types of firm-specific news (the last two columns).[22]

Of course, it is possible that lower-priced stocks simply have more extreme news events. However, it is worth emphasizing that the sample used in this analysis only includes S&P 500 firms, which represent the largest firms in the US economy. Among these firms, it seems plausible that the distribution of news events would be similar across levels of nominal price. This analysis using S&P 500 firms again shows that the predictions from Section 2 apply to the largest stocks in the US economy.

5.2 Earnings Announcements

5.2.1 Initial Response to Earnings Announcements

Another important and easily identifiable source of firm-specific news comes from pre-scheduled quarterly earnings announcements. Therefore, we also estimate Equation 9 using earning announcements as the news events. The results are shown in Table 9, Panel A. We find that cumulative abnormal returns around days with earning announcements are also significantly more extreme

[21] Abnormal returns are computed relative to the market model, where market betas are estimated based on returns from dates $t-150$ to $t-50$.

[22] Categories of news defined by Boudoukh et al. (2018) include *Business Trends, CSR Brand, Capital Returns, Deals, Earnings Factors, Employment, Facility, Financial, Financing, Forecast, General, Investment, Legal, Mergers & Acquisitions, Product, Ratings, Stock, and Stock Holdings.*

for lower-priced stocks. The magnitudes are similar to those in Table 8, which focused on news identified through textual analysis.

Of course, it is again possible that lower-priced stocks have more extreme news—in this case about earnings. Fortunately, we can observe and control for the extremity of earnings news. As described in Section 3, we compute standardized unexpected earnings (SUE) as a measure of the magnitude of an earnings surprise, given the distribution of analyst forecasts prior to the announcement. Because our measure of earnings surprises requires multiple recent analysts forecasts, it is only available for a subset of the earnings announcements from Panel A of Table 9. Within this sample, we test whether the return response to the same earnings surprise is greater for lower-priced stocks. Specifically, we estimate equations of the form:

$$\begin{aligned} log(1 + CAR_{i,[t-1,t+1]}) = \beta_1 DecileRankSUE_{it} + \beta_2 log(\ddot{Price}_{i,t-2}) + \beta_3 log(\ddot{Size}_{i,t-2}) + \\ \beta_4 log(\ddot{Price}_{i,t-2}) \times DecileRankSUE_{it} + \\ \beta_5 log(\ddot{Size}_{i,t-2}) \times DecileRankSUE_{it} + \epsilon_{i,t}, \end{aligned} \quad (10)$$

where for stock i with an earnings announcement at date t, $CAR_{i,[t-1,t+1]}$ represents the cumulative abnormal return following the announcement from date $t-1$ to date $t+1$, $DecileRankSUE_{it}$ represents the decile rank of the earnings surprise, $log(\ddot{Price}_{i,t-2})$ represents the demeaned log price prior to the earnings announcement, and $log(\ddot{Size}_{i,t-2})$ represents the demeaned log size prior to the earnings announcement. The price and size variables are demeaned so that β_1 can be interpreted as the return response for a stock of average price and size.

The results are shown in Panel B of Table 9. First, without size controls in column (1), the positive β_1 coefficient implies that, for a stock of average size and price, a 1 unit increase in SUE decile rank is associated with a 74.1 basis point increase in the return response to the earnings announcement. The negative β_4 coefficient implies that for a one log point increase in price, a 1 unit increase in SUE decile rank is associated with a return response that is 22.3 basis points smaller. These estimates imply that $\theta \approx 0.30$ (=22.3/74.1), which is again very similar to what we find in our other analyses. In column (2), we repeat the same analysis but replace the price variables with analogous size variables. In this case, we estimate β_1 to be positive and β_5 to be negative (both at the 1% level). Thus, it does appear that larger stocks are also less responsive to earnings surprises. However in column (3), when we include both price and size variables in the regression, our estimate of β_4 remains similar to that from column (1), but our estimate of β_5 becomes smaller by an order of magnitude and statistically insignificant. Thus, price is predictive of responsiveness to earnings news, even controlling for size. In addition, size is not predictive of responsiveness to earnings news, once one controls for price. In columns 4–6, we show that the results remain similar when we slightly widen the window over which the initial return response is measured from dates $t-10$ to $t+20$. This shows that our results are not driven by a short-term drop in liquidity in the days immediately around the earnings announcement. Overall, these results indicate that the initial return response to the same earnings surprise is greater for lower-priced stocks, which is what we would expect under non-proportional thinking.

5.2.2 Post Earnings Announcement Drift

Previous research on post earnings announcement drift (see e.g., Bernard and Thomas, 1990) has shown that, in general, investors underreact to earnings announcements initially, such that subsequent returns continue to drift in the same direction as the initial return response. Since non-proportional thinking predicts stronger initial return responses to earnings news for lower-priced stocks, we would expect lower-priced stocks to exhibit less drift. We note that this is a sharp prediction: we usually expect asset pricing anomalies to be stronger among lower-priced stocks due to correlated microstructure frictions or liquidity considerations. However, non-proportional thinking predicts *weaker* drift among lower-priced stocks.

In Table 10, we estimate equations of the form:

$$\begin{aligned} log(1+CAR_{i,[t+2,\tau]}) = \beta_1 log(1+CAR_{i,[t-1,t+1]}) + \beta_2 log(\ddot{Price}_{i,t-2}) + \beta_3 log(\ddot{Size}_{i,t-2}) + \\ \beta_4 log(\ddot{Price}_{i,t-2}) \times log(1+CAR_{i,[t-1,t+1]}) + \\ \beta_5 log(\ddot{Size}_{i,t-2}) \times log(1+CAR_{i,[t-1,t+1]}) + \epsilon_{it}, \quad (11) \end{aligned}$$

where for stock i with an earnings announcement at date t, $CAR_{i,[t+2,\tau]}$ represents drift, i.e., cumulative abnormal returns following the announcement from date $t+2$ to date $\tau \in \{10, 20, ..., 60\}$, $CAR_{i,[t-1,t+1]}$ represents the initial return response to the earning announcement from date $t-1$ to date $t+1$, $log(\ddot{Price}_{i,t-2})$ represents the demeaned log price prior to the earnings announcement, and $log(\ddot{Size}_{i,t-2})$ represents the demeaned log size prior to the earnings announcement. Abnormal returns are computed relative to the market model, where market betas are estimated based on returns from dates $t-150$ to $t-50$. The price and size variables are again demeaned so that β_1 can be interpreted as the level of drift for a stock of average price and size. We also control for the direct effects of price and size on expected returns. The coefficients on the interaction terms β_4 and β_5 measure how PEAD varies with price and size, respectively.

Table 10 shows the results. We estimate β_1 to be positive and statistically significant at various horizons. Consistent with the PEAD literature, this means that for an average stock, the initial return response to an earnings announcement predicts the subsequent return response. More importantly, we also estimate β_4 to be positive and statistically significant. Consistent with the non-proportional thinking hypothesis, this means that drift is indeed stronger for higher-priced stocks, or equivalently, that drift is weaker for lower-priced stocks.[23]

5.3 Reversals

Previous research has also suggested that investors sometimes overreact to news leading to subsequent reversals (De Bondt and Thaler, 1985). Under non-proportional thinking, we would expect that overreaction and subsequent reversals would be stronger for lower-priced stocks. To examine whether lower-priced stocks experience stronger reversals, we follow the methodology of De Bondt and Thaler (1985).[24] Specifically, we first sort stocks in each year-month t by past cumulative abnormal returns over the interval $[t-36, t-1]$. Our winners portfolio consists of all stocks in the top decile of past performance, and our losers portfolio consists of all stocks in the bottom decile of past performance. This sorting is more inclusive than the original De Bondt and Thaler (1985),

[23] We also estimate β_5 to be negative and statistically significant, implying that drift is stronger for smaller stocks.

[24] An important caveat is that the existence of a return correction does not imply that the non-proportional thinking bias goes to zero in future periods. Even as the misreaction to previous news is corrected, investors can again under- or overreact to future news due to non-proportional thinking.

which only focused on the extreme top 35 winner and loser stocks. Like De Bondt and Thaler, we interpret stocks in these portfolios to be stocks that have experienced extreme news. We then partition the winner and loser portfolios into quintiles in terms of lagged share price as of month $t-37$, which precedes the period used to categorize winners and losers.

The cumulative abnormal returns to holding equal-weighted winner and loser portfolios in each lagged share price quintile are presented in Figure 11. We are able to replicate the original De Bondt and Thaler long-run reversal result with our updated data: the past winners portfolio experiences subsequent negative abnormal returns and the past losers portfolio experiences subsequent positive abnormal returns. More interestingly, we can sort the magnitude of the long-run reversal by lagged share price. We find that the lowest quintile of stocks in terms of lagged nominal share price corresponds to the most extreme outperformance among the past losers portfolio. Similarly, the lowest quintile of stocks by share price also corresponds to the most extreme underperformance among the past winners portfolio. Further, the magnitude of the long-run reversal within the past winners and past losers portfolios can almost perfectly be ordered by lagged share price (the only exception being price quintiles 3 and 5 in the winners portfolio, which are crossed). In general, as price increases, the absolute magnitude of the reversal decreases. These results are consistent with the idea that the market is more likely to overreact to news for lower-priced stocks, as we would expect under non-proportional thinking.

Finally, we show that the magnitude of the long-run reversal varies significantly with lagged price and substantially less so with lagged size. Table 11, columns (1)–(3), show regressions of future abnormal returns on past abnormal returns and the interaction between past abnormal returns and lagged price and/or size. The regressions also control for the direct effects of lagged price and size. To account for time variation in the level of returns, as well as time variation in the overall magnitude of the reversal phenomenon, we estimate this regression using the standard Fama-MacBeth methodology in asset pricing.[25] Lagged price and size are measured as of the end of month $t-37$. We find that the direct effect of past returns on future returns is negative, consistent with

[25]This is equivalent to estimating a cross-sectional regression for each time period, and reporting the simple average of the coefficients across time periods. This approach is similar to allowing for a time period fixed effect and time fixed effects interacted with all explanatory variables, and reporting the average coefficients across time.

a long-run reversal. The interaction term in column (1) shows that the absolute magnitude of the reversal decreases significantly with lagged price. Column 2 shows that the reversal also decreases with lagged size. Most interestingly, column (3) shows that, when we allow the magnitude of the return reversal to vary with both price and size, we find that it is strongly related to price, and almost unrelated to size.

In columns (4)—(6), we find similar results when examining the reversal pattern in a shorter window, following the methods in Jegadeesh (1990). We continue to find in columns (4)—(6) that the magnitude of the short-run reversal is strongest for lower-priced stocks, and is more strongly related to lagged price than lagged size.

6 Conclusion

We hypothesize that investors in financial markets engage in non-proportional thinking—they think that news should correspond to a dollar change in price rather than a percentage change in price, leading to more extreme return responses to news for lower-priced stocks. Consistent with non-proportional thinking, we find that total volatility, idiosyncratic volatility, and market beta are significantly higher for stocks with lower share prices. To identify a causal effect of price, we show that volatility increases sharply following stock splits and drops following reverse stock splits. Further, non-proportional thinking leads to more extreme return responses to news identified through textual analysis or earnings announcements for lower-priced stocks. The economic magnitudes are large: a doubling in a stock's nominal price is associated with a 20-30% decline in its volatility, beta, and return response to firm-specific news.

Our analysis shows that non-proportional thinking is an important determinant of cross-sectional variation in volatility and beta. Well-known asset pricing patterns such as the leverage effect and the negative relation between size and risk (volatility or beta) can be reinterpreted through the lens of non-proportional thinking. We also show that non-proportional thinking can contribute to over- and underreaction to news and subsequent reversals and drift. The existing behavioral finance literature has mainly focused on limited attention or belief errors regarding the persistence of news shocks to explain these patterns. Non-proportional thinking offers a complementary explanation:

over and under-reaction to news and consequent reversals and drift can also be caused by investors thinking in the wrong units.

Our results raise an interesting question of whether managers hold mistaken beliefs when they consider whether to engage in stock splits. When asked for the rationale behind split decisions, managers frequently refer to the desire for a broader investor base and increased liquidity (Baker and Gallagher, 1980). These beliefs contradict the empirical evidence showing that splits substantially raise return volatility without increasing liquidity. On the other hand, many managers hold a significant portion of their personal wealth in firm stock options. Therefore, it is possible that they use splits as a way of increasing the value of their options by increasing volatility.

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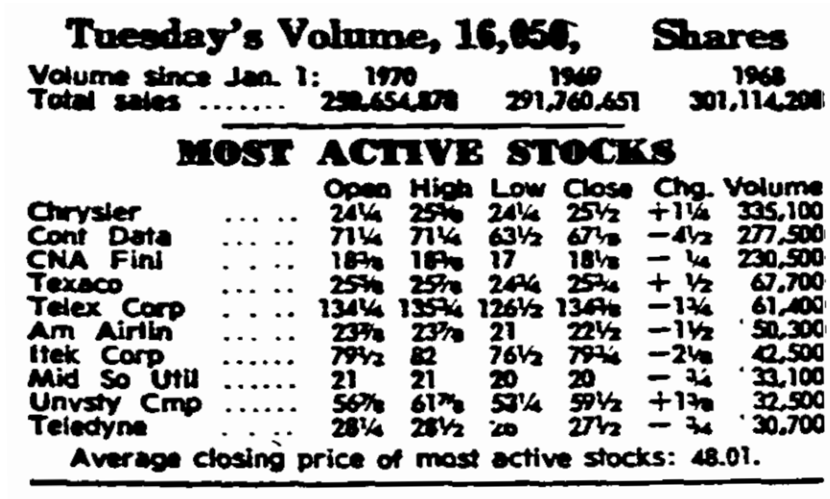
Figure 1
Display of Changes in the Value of Stocks

Panel A: Wall Street Journal, 1970



Tuesday's Volume, 16,050, Shares

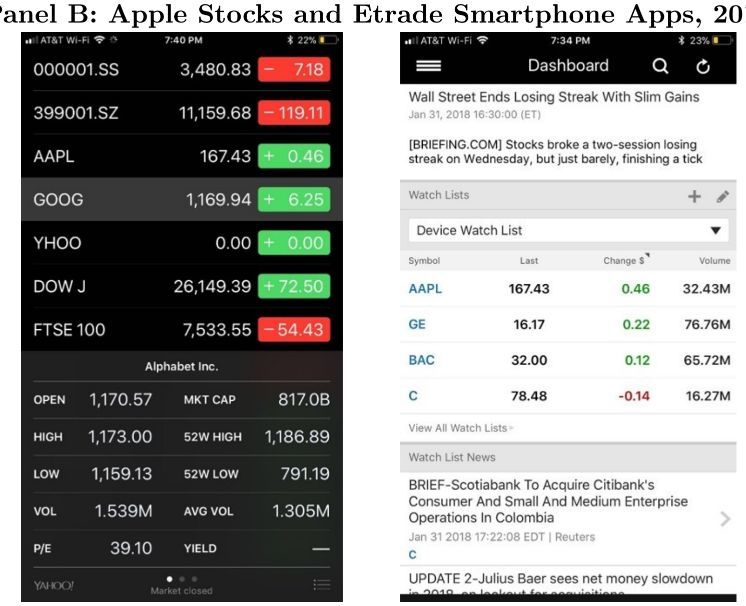
Volume since Jan. 1:	1970	1969	1968
Total sales	250,654,878	291,760,651	301,114,208

MOST ACTIVE STOCKS

	Open	High	Low	Close	Chg.	Volume
Chrysler	24¼	25⅝	24¼	25½	+1¼	335,100
Cont Data	71¼	71¼	63½	67⅛	−4½	277,500
CNA Finl	18⅜	18⅝	17	18⅛	− ¼	230,500
Texaco	25⅝	25⅞	24¾	25¾	+ ½	67,700
Telex Corp	134¼	135¾	126½	134⅜	−1¾	61,400
Am Airlin	23⅝	23⅞	21	22½	−1½	50,300
Itek Corp	79½	82	76½	79¾	−2⅛	42,500
Mid So Util	21	21	20	20	− ¾	33,100
Unvsty Cmp	56⅞	61⅞	53¼	59½	+1⅜	32,500
Teledyne	28¼	28½	20	27½	− ¾	30,700

Average closing price of most active stocks: 48.01.

Panel B: Apple Stocks and Etrade Smartphone Apps, 2017

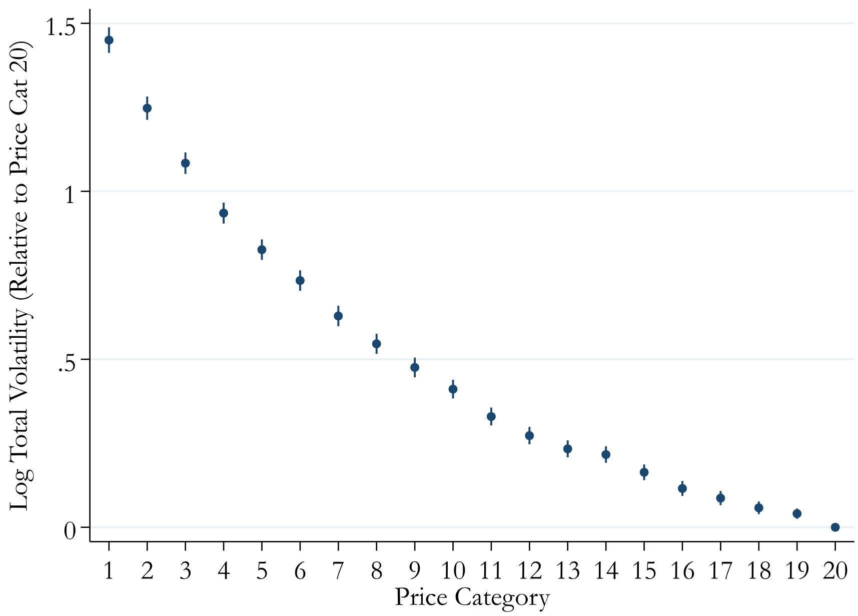


Panel C: CNBC Ticker, 2016

Figure 2
Shape of Volatility-Price Relation

Panel A of this figure shows the non-parametric shape of the volatility-price relation. It repeats the regression from Panel A of Table 2 column (4), which controls for size categories and year-month fixed effects, replacing the continuous Log(Lagged Price) variable with 20 lagged share price bin indicators, with each bin containing the same number of observations. The resulting coefficients are plotted with vertical bars indicating 95% confidence intervals. Quantile 20 is omitted. Panel B repeats the analysis of Panel A, with the modification that each bin represents an equal range of logged prices, again controlling for size and time fixed effects. The omitted category represents log lagged share price in the range of 5.0 to 5.25. Standard errors are double-clustered by stock and year-month.

Panel A: Equally-Spaced Price Bins, Controlling for Size



Panel B: Log-Log Volatility and Price Relation, Controlling for Size

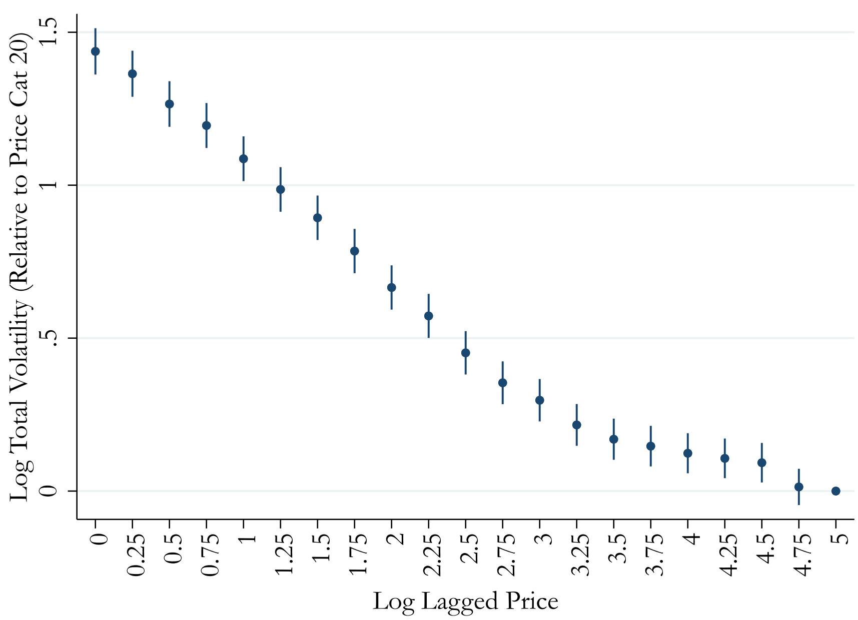


Figure 3
Cross-Sectional Estimation

For each of the 1,085 calendar year-months in our data sample, we estimate a cross-sectional regression of log volatility on lagged log price, controlling for 20 size categories. This figure plots a histogram of the estimated coefficients on lagged log price from the 1,085 regressions. The mean of the coefficients is -0.31, and the standard deviation is 0.10.

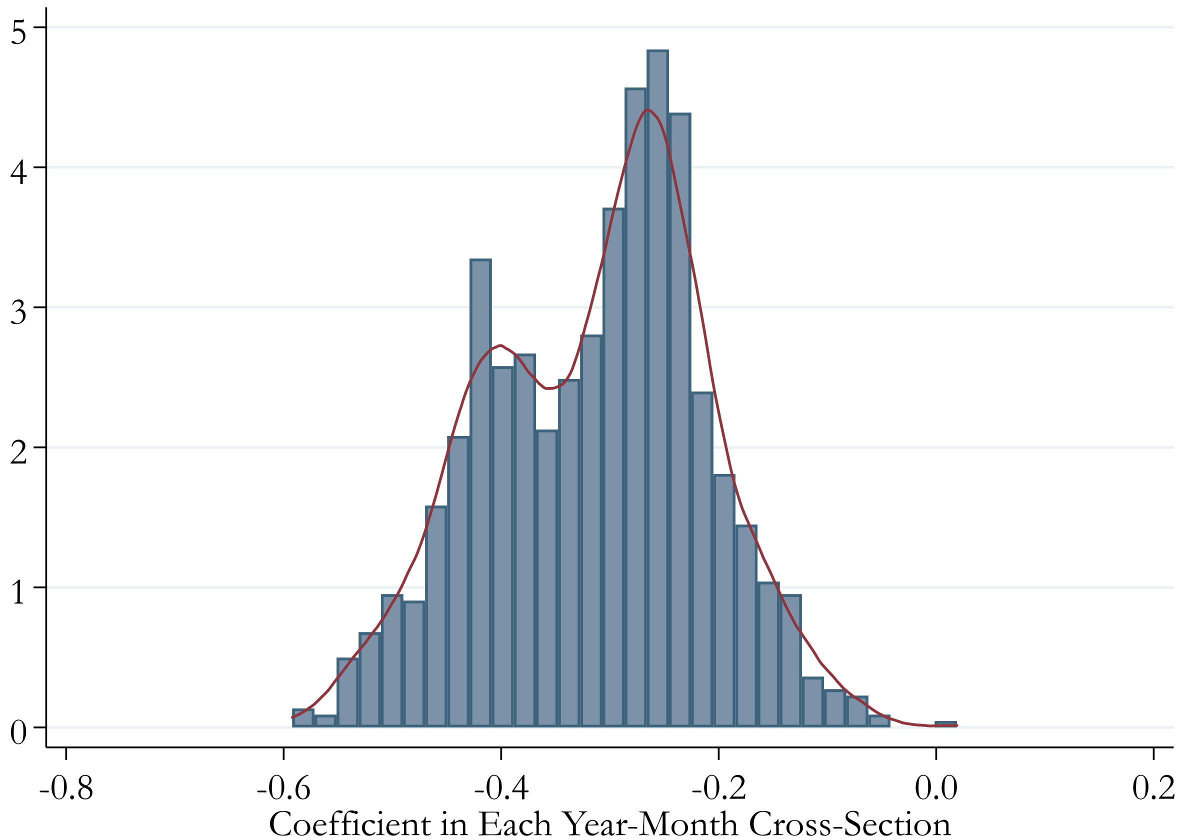
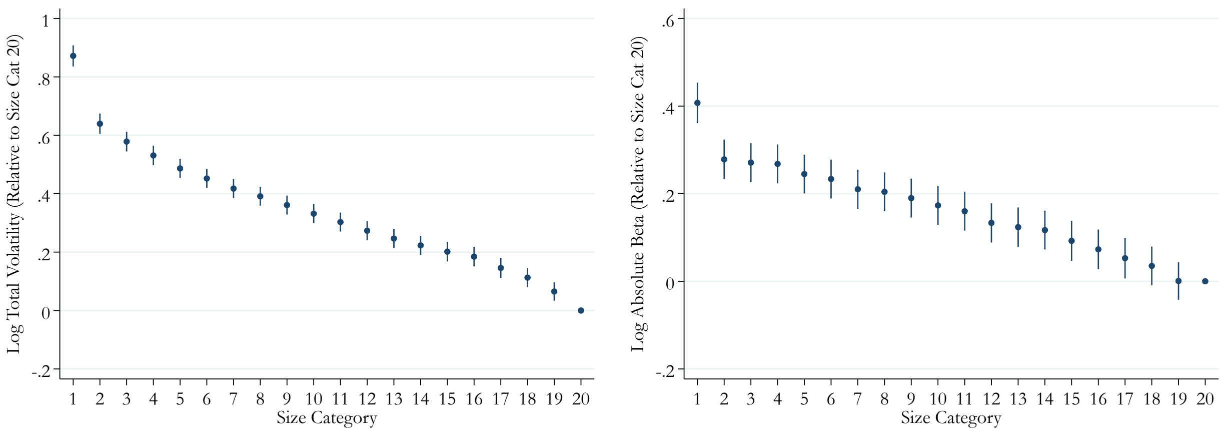


Figure 4
How Price Affects the Size-Volatility and Size-Beta Relations

This figure explores the extent to which nominal price differences explain the negative volatility-size and beta-size relations. Panel A shows the coefficients from a regression of log volatility or log absolute beta on 20 size category indicators (defined using the Fama French size category cutoffs in the corresponding year-month, with the largest size bin as the omitted category) as of the end of the previous month, after controlling for year-month fixed effects. Panel B shows the same set of coefficients after adding in a single additional control variable for the log of the lagged nominal share price. The dots represent the coefficient estimates and the vertical lines represent 95% confidence intervals. Standard errors are double-clustered by stock and year-month.

Panel A: Size-Volatility and Size-Beta Relations, Without Controlling for Price



Panel B: Size-Volatility and Size-Beta Relations, Controlling for Price

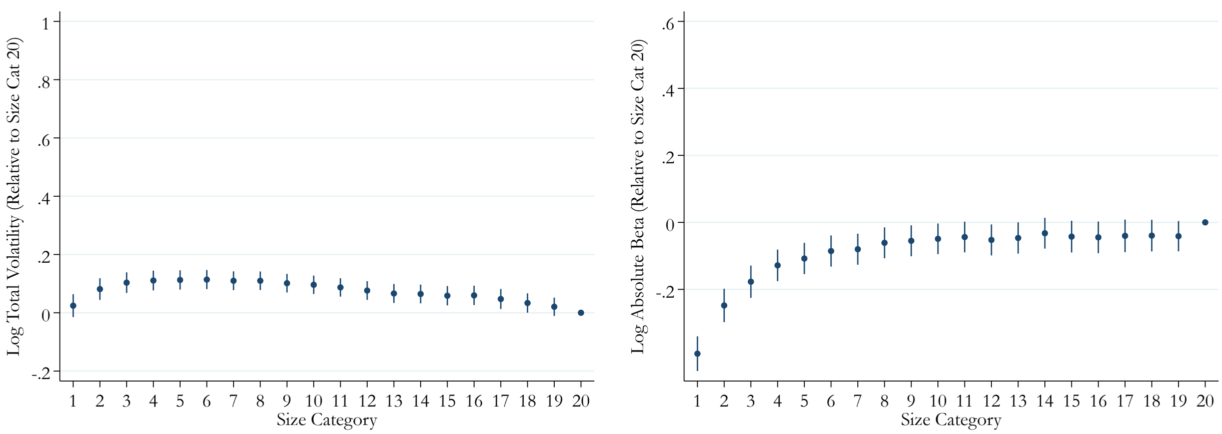


Figure 5

Regression Discontinuity: Intraday Price Range Around Stock Splits

This figure shows changes in volatility around 2-for-1 stock splits. It examines 45 days before and after the pre-announced split execution date. Volatility is proxied for by the intraday price range percentage, defined as $100 \times \frac{High-Low}{High}$. The day of the split execution event is excluded. The thick lines represent non-parametric estimates of the mean on a given day, estimated using a local linear regression with a triangular kernel and MSE-optimal bandwidth. The thin lines represent 95% confidence intervals. The dots show raw means for each event day.

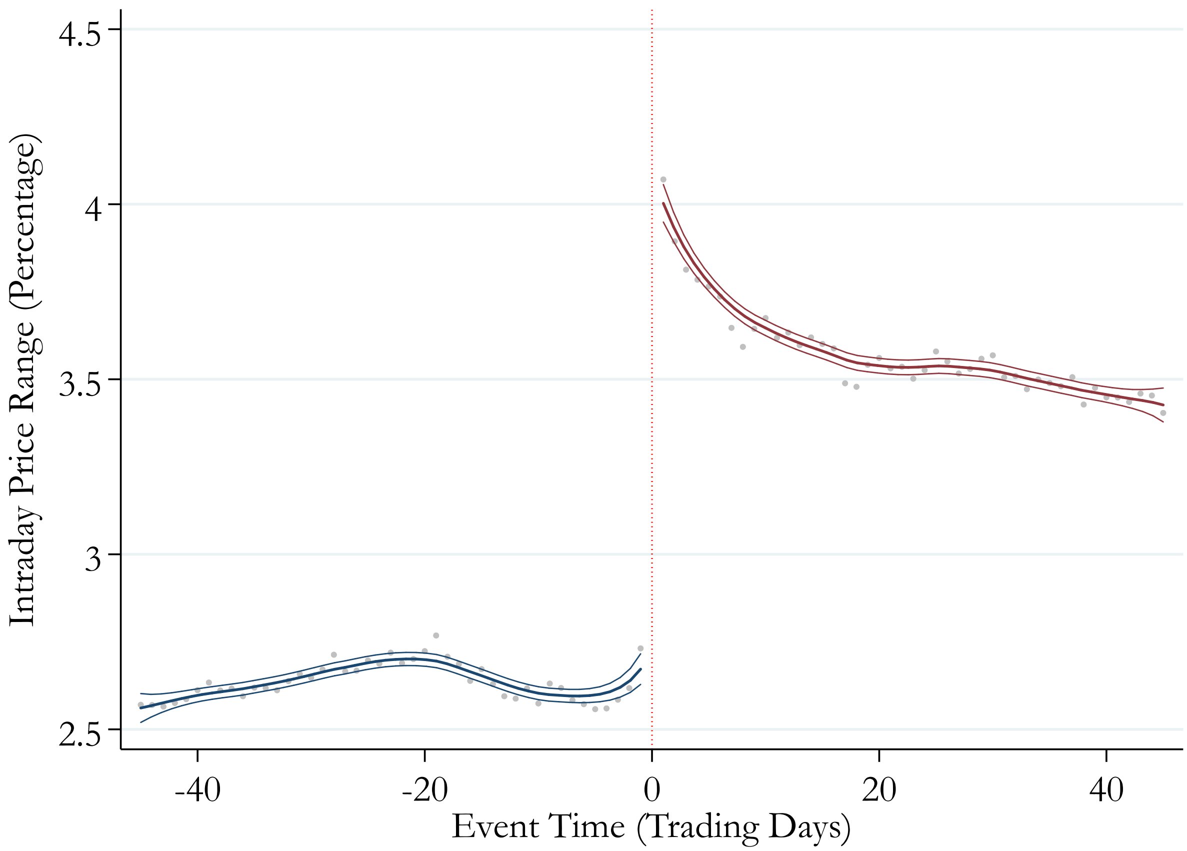


Figure 6

Event Study: Volatility and Beta Around Stock Splits

This figure show changes in total volatility (Panel A), idiosyncratic volatility (Panel B), and market beta (Panel C) in each event-month around stock splits. Observations are at the stock-month level, and the sample is limited to the six months before and after a split. Event month -1 is the omitted category. Dots in the left graphs represent the point estimates for the β_k coefficients in Equation 7 (Single Difference), separately for 2-for-1 and 3-for-2 splits. Dots in the right graphs represent the point estimates for the β_k coefficients in Equation 8 (Difference-in-Differences). The vertical lines represent 95% confidence intervals. The coefficient β_0 is not shown, since event month $k = 0$ contains both pre-split and post-split days. Standard errors are double-clustered by stock and year-month.

Panel A: Total Volatility

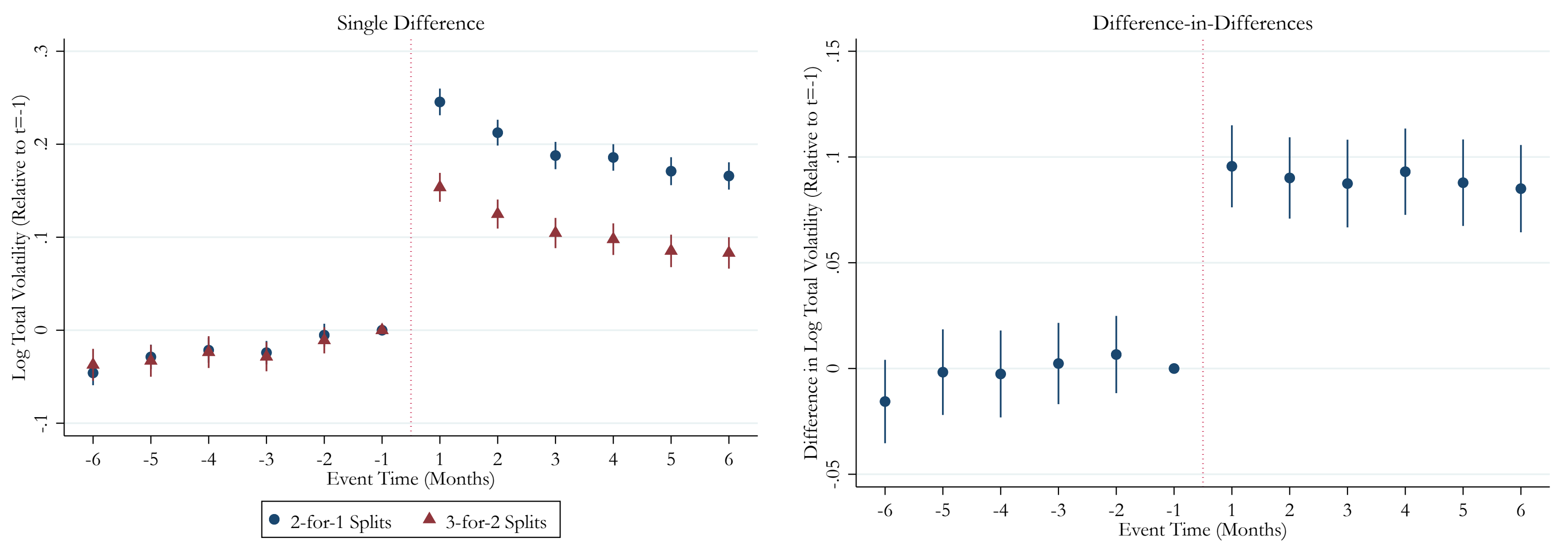
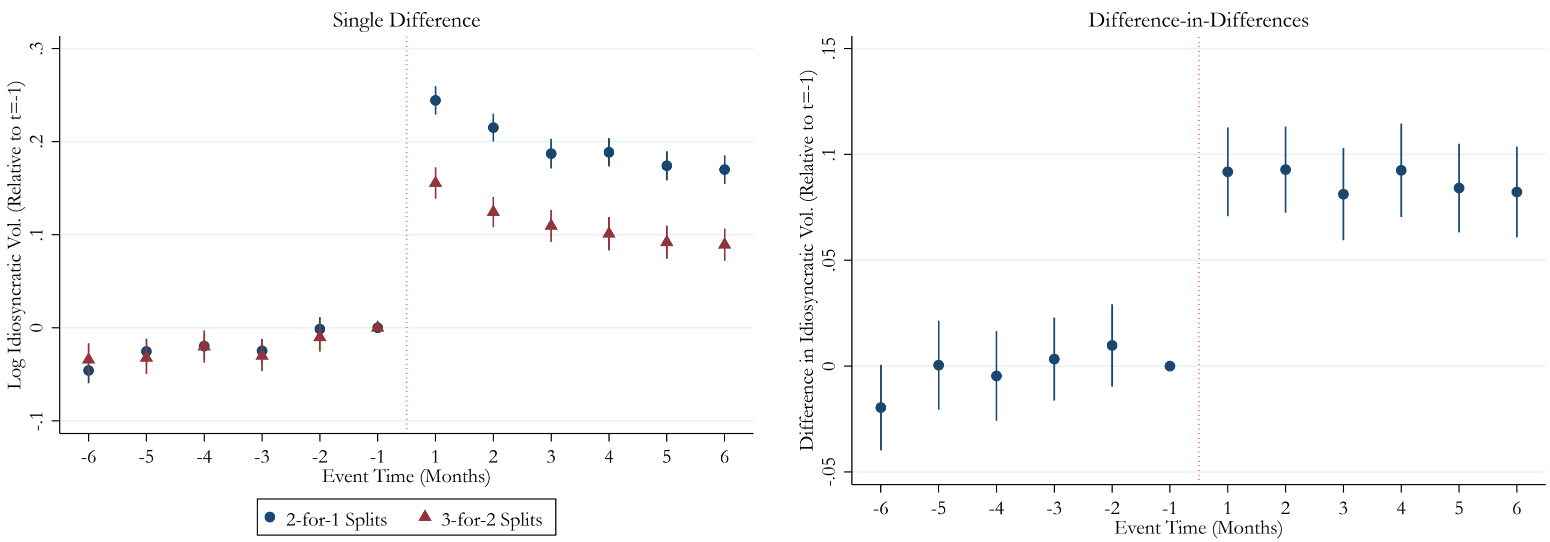


Figure 6
(Continued)

Panel B: Idiosyncratic Volatility



Panel C: Market Beta

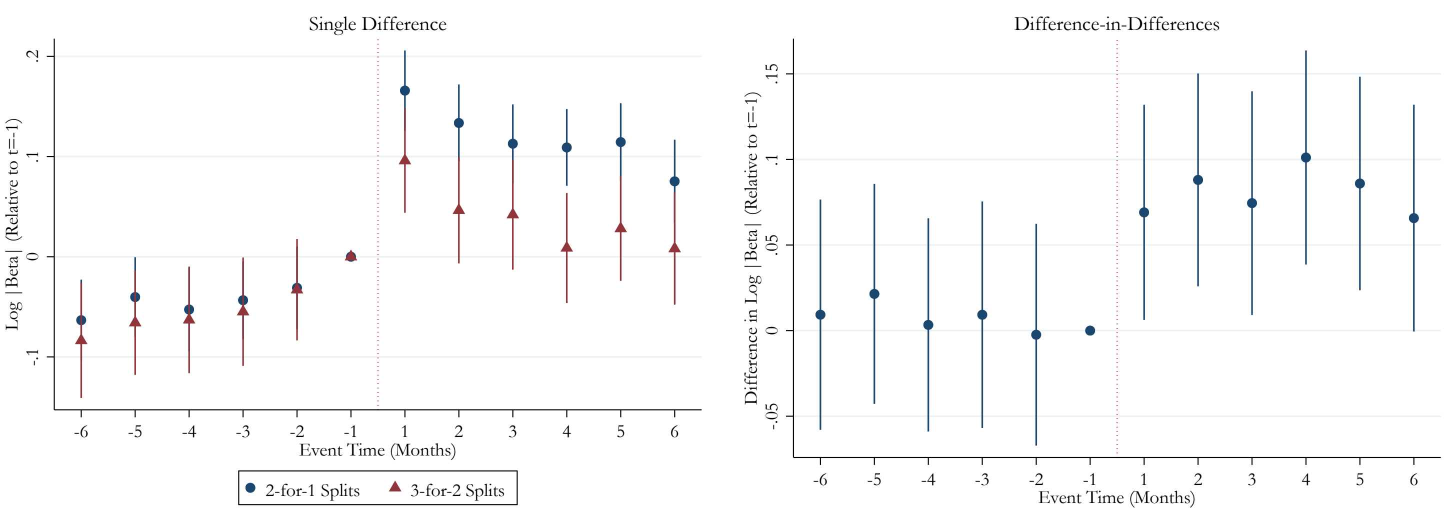


Figure 7

Event Study: Volume Around Stock Splits

This figure shows how volume changes around splits. We repeat the analysis in Figure 6, with total volume turnover as the dependent variable.

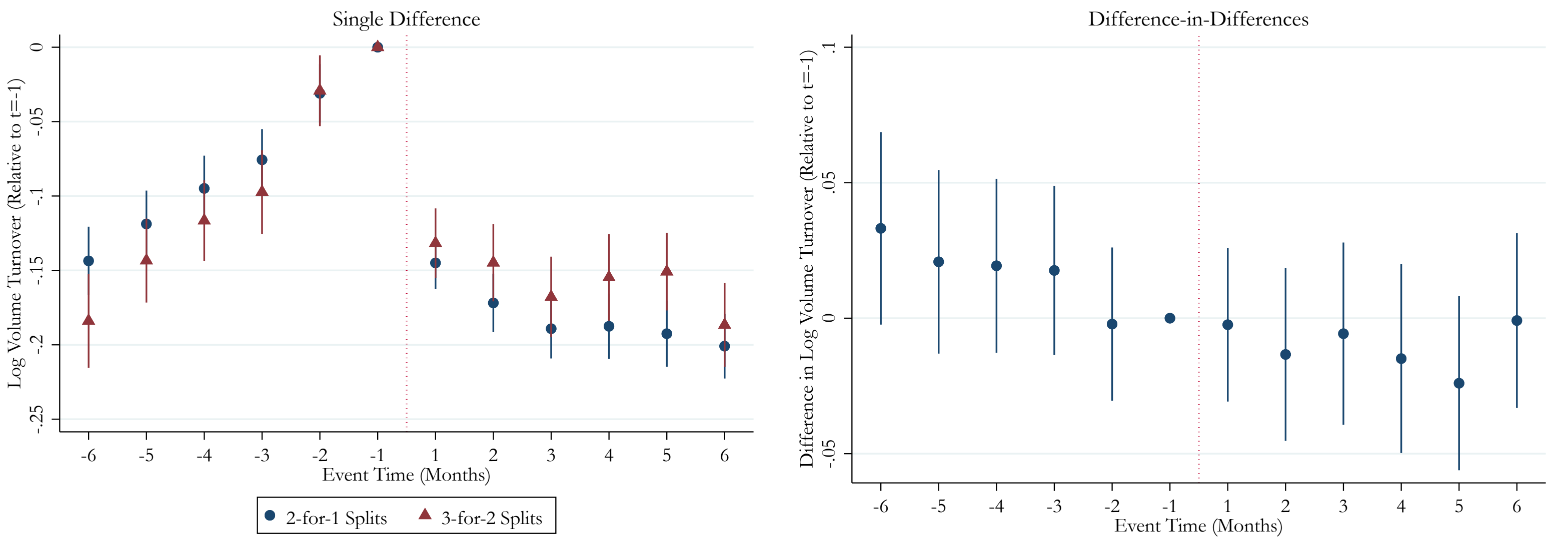
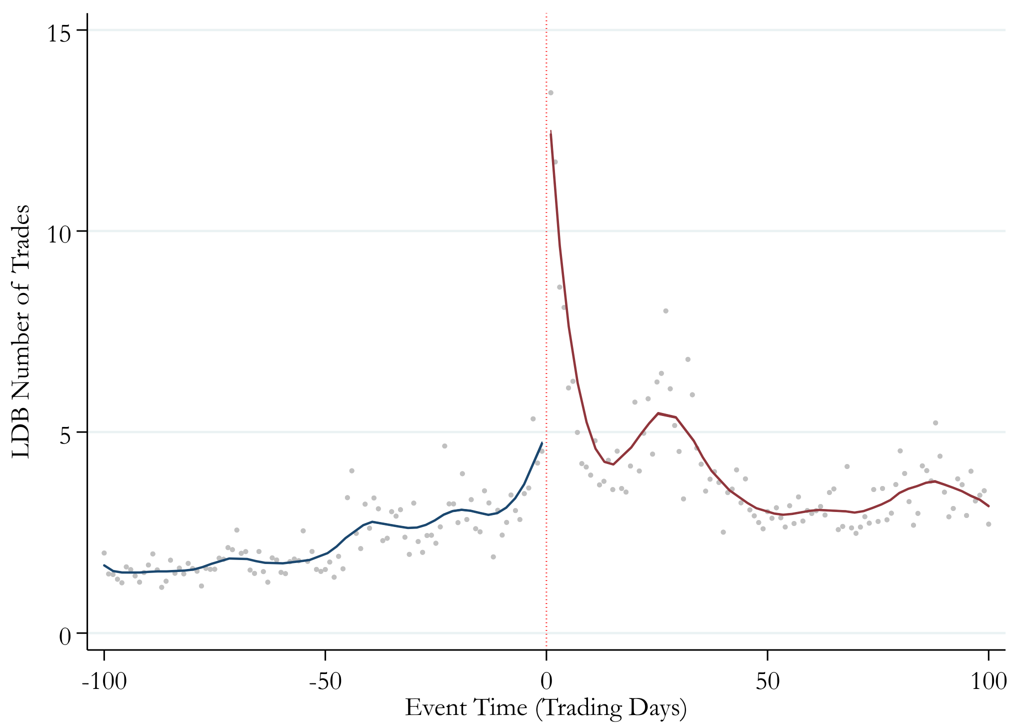


Figure 8
Retail Trading Activity Around Splits

This figure shows changes in retail trading frequency around 2-for-1 stock splits. The data comes from Odean (1998) and covers all retail trades for a large discount broker (LDB). In Panel A, the dots show the number of executed trades by LDB clients. In Panel B, the dots show the number of executed buy orders by LDB clients. In Panel C, the dots show the number of executed sell orders by LDB clients. The lines come from local linear regressions estimated with a 10-day bandwidth and triangular kernel. The dots show raw means for each event day.

Panel A: Number of Executed Trades by LDB Clients



Panel B: Number of Executed Buy and Sell Orders by LDB Clients

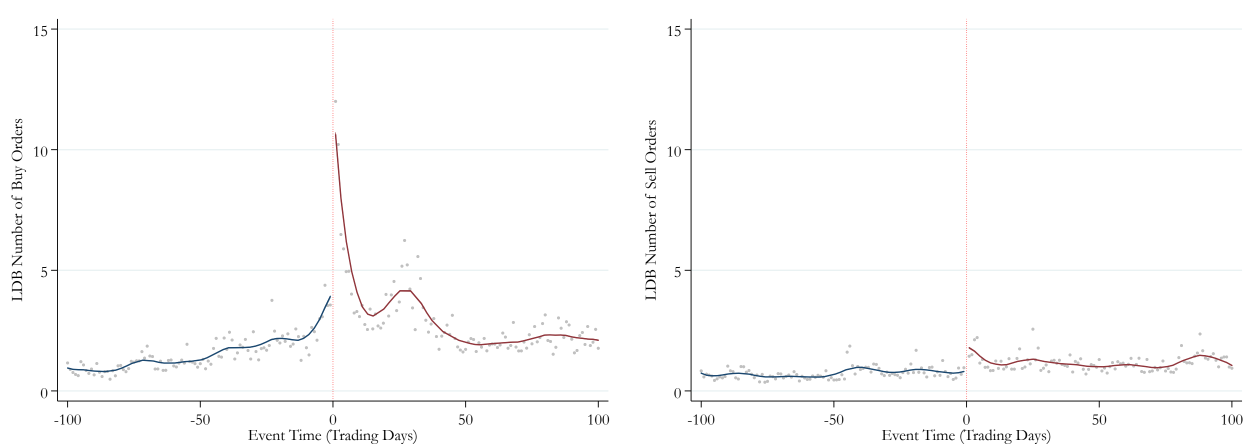


Figure 9
Nature of Retail Investors Holding Stocks Around Splits

This figure shows changes in retail ownership around 2-for-1 stock splits. The data comes from Odean (1998) and covers all retail trades for a large discount broker (LDB). The dots show the mean income of associated LDB accounts that hold the stock around the split event. The inner lines come from local linear regressions estimated with a 10-day bandwidth and triangular kernel. The outer lines represent 95% confidence intervals. The raw data provide income ranges rather than exact income. Following Barber and Odean (2001), we assign income according to the midpoint of an individual's income range. We classify individuals in the top income range (>$125,000) as having an income of $137,500.

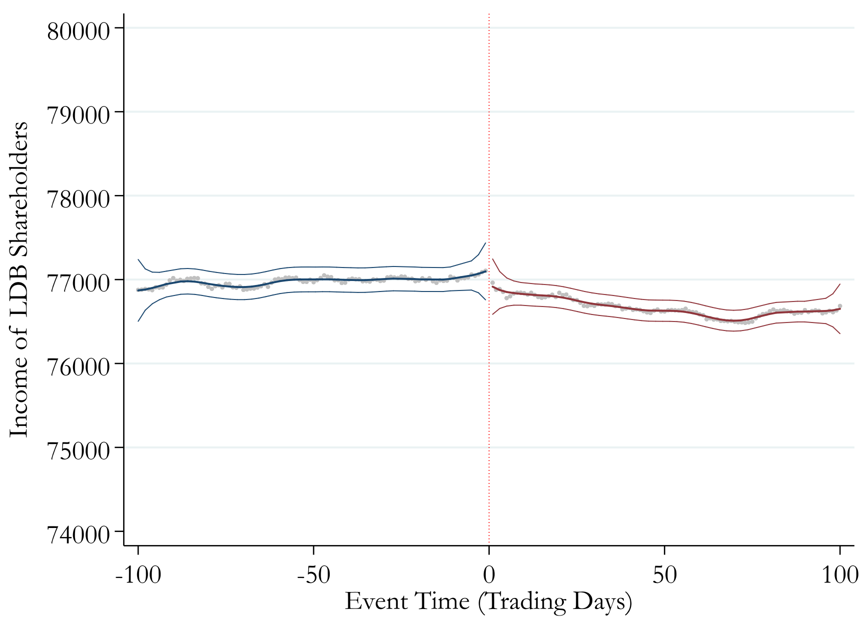
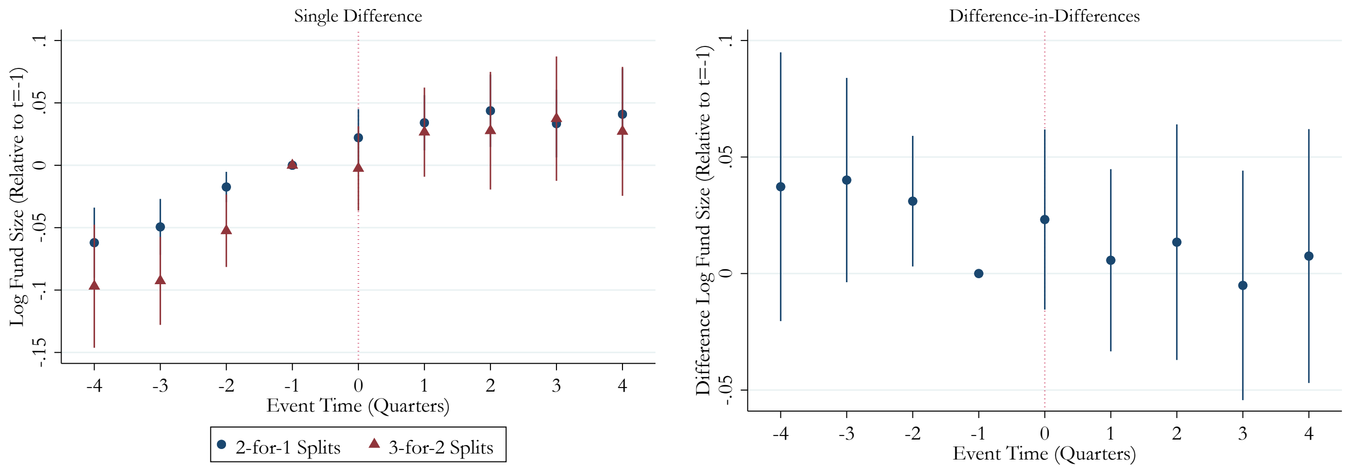


Figure 10

Nature of Mutual Funds Holding Stocks Around Splits

This figure shows how the nature of mutual funds holding each stock changes around stock splits. We repeat the analysis in Figure 6, with the log of the average size of mutual funds holding the stock and the log of the average concentration of mutual funds holding the stock as the dependent variables in Panels A and B, respectively. Both averages are weighted by the size of mutual funds' positions in the stock. Concentration is measured as the Herfindahl index of the funds' positions.

Panel A: Mutual Fund Size



Panel B: Mutual Fund Concentraion

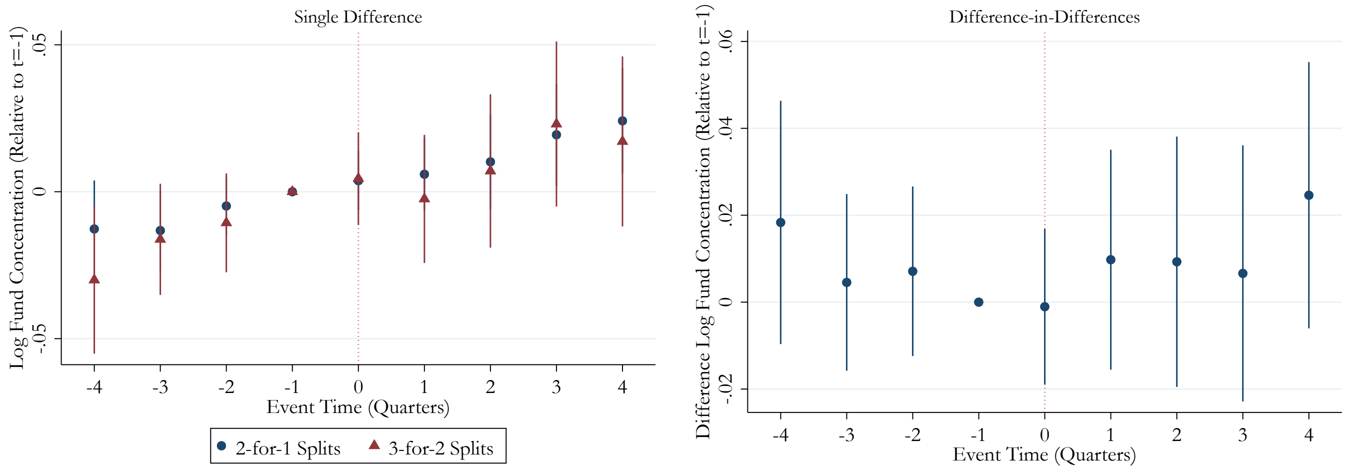


Figure 11
Long-Run Reversal, Sorted by Lagged Price

This figure plots cumulative abnormal returns to holding equal-weighted winner and loser portfolios in each lagged share price quintile. Stocks are first sorted in each year-month t by past cumulative abnormal returns over the interval $[t-36, t-1]$. The winners portfolio consists of all stocks in the top decile of past performance, and the losers portfolio consists of all stocks in the bottom decile of past performance. The winner and loser portfolios are then partitioned into quintiles in terms of lagged share price as of month $t-37$, which precedes the period used to categorize winners and losers. Past performance and subsequent cumulative abnormal returns are measured using market-adjusted returns as in De Bondt and Thaler (1985).

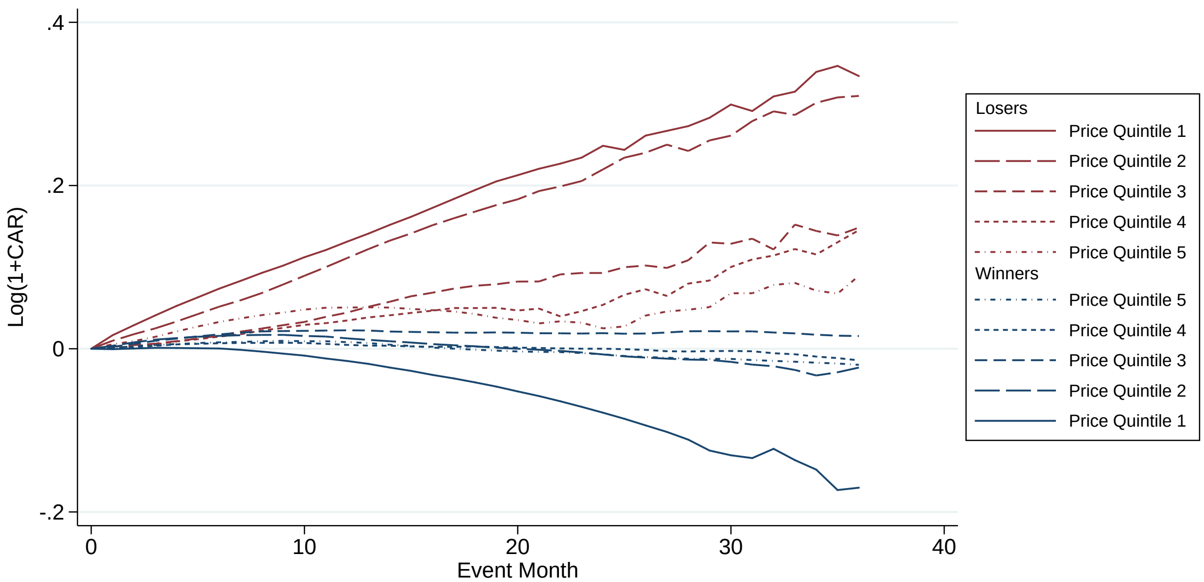


Table 1
Summary Statistics

Observations are at the stock-month level. Total volatility is the annualized standard deviation of daily returns within a month. A stock's market beta in a month is estimated by regressing its daily excess returns on market excess returns. To account for non-synchronous prices we include both current and 4 lagged market excess returns in the regressions, estimating beta as the sum of the slopes on all lags, imposing the constraint that lags 2–4 have the same slope (Lewellen and Nagel, 2006). Idiosyncratic volatility is the annualized standard deviation of the residuals from these regressions. Price is the stock's nominal price on the last day of the month. Market capitalization is the product of price and shares outstanding. Institutional ownership is the sum of the number of shares of each stock held by 13f filers, divided by its shares outstanding, as of the end of the most recently completed quarter. Sales volatility is the standard deviation of year-over-year quarterly sales growth during the previous four quarters. Volume turnover is the number of shares traded in each month divided by the total number of shares outstanding. The market-to-book ratio is market capitalization (csho*prcc_f) plus the book value of assets (at) less shareholder equity (seq), all divided by the book value of assets (at). Book leverage is short-term and long-term debt (dlc+dltt) divided by the book value of assets (at). The bid-ask spread percentage is $100 \times \frac{Ask-Bid}{Ask}$. The intraday price range percentage is $100 \times \frac{High-Low}{High}$. Panel B shows the correlations between our main variables of interest. All variables in Panel B are measured in the same way as they are measured in the regression analysis in the paper.

Panel A: Summary

	Obs	Mean	Median	Std Dev
Total Volatility (Annualized)	3,254,302	0.510	0.390	0.450
Idiosyncratic Volatility (Annualized)	3,254,302	0.448	0.334	0.415
Market Beta	3,254,302	0.941	0.809	3.069
Price	3,254,302	18.85	13.50	19.13
Market Capitalization (Millions)	3,254,302	1179.9	64.47	8800.6
Insitutional Ownership	2,165,251	0.346	0.272	0.292
Sales Volatility	2,316,178	0.273	0.0966	0.691
Volume Turnover	2,996,292	0.0882	0.0382	0.204
Market-to-Book Ratio	2,240,583	1.977	1.252	18.19
Book Leverage	2,130,604	0.232	0.191	0.278
Bid Ask Spread (Percentage)	2,246,545	4.840	2.525	17.63
Intraday Price Range (Percentage)	2,555,175	3.586	2.826	2.726

Table 1

(Continued)

Panel B: Correlations

	Price	Vol	Mkt Cap	Sales Vol	Return	MTB	Volume	BA Spread	Leverage
Log(Lagged Price)	1								
Log(Total Volatility)	-0.578	1							
Log(Lagged Market Capitalization)	0.656	-0.329	1						
Log(Lagged Sales Volatility)	-0.316	0.300	-0.258	1					
Log(1+Lagged 12-Month Return)	0.434	-0.317	0.219	-0.116	1				
Lagged Market-to-Book Ratio	0.00684	0.0143	0.0205	0.163	0.0212	1			
Lagged Volume Turnover	0.0438	0.106	0.168	0.0624	0.0195	0.0150	1		
Lagged Bid-Ask Spread Percentage	-0.197	0.120	-0.200	0.0387	-0.234	-0.00275	-0.0419	1	
Lagged Book Leverage	-0.0828	0.0322	-0.0289	-0.000293	-0.0799	0.00322	-0.0208	0.0198	1

Table 2
Baseline Results: Total Volatility

This table explores how return volatility varies with share price. Using data at the stock-month level, regressions of the following form are estimated:

$$log\,(vol_{i,t}) = \beta_0 + \beta_1 log\,(price_{i,t-1}) + controls + \tau_t + \epsilon_{it},$$

where $vol_{i,t}$ represents the volatility of stock i in month t, $price_{i,t-1}$ represents the stock's price at the end of month $t-1$, and τ_t represents year-month fixed effects. Total volatility is the annualized standard deviation of daily returns within a month. Control variables can include the log of the firm's size (measured as total market equity) at the end of the previous month or indicator variables for 20 size categories based on the market capitalization of the stock relative to the size breakpoints for each year-month from the Ken French Data Library. The sample excludes observations with extreme lagged prices (the bottom and top 1% of prices each month). Standard errors are double-clustered by stock and year-month. *,**, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Panel A: Cross-Section

	Log(Total Volatility)			
	(1)	(2)	(3)	(4)
Log(Lagged Price)	-0.326***		-0.332***	-0.339***
	(0.00339)		(0.00446)	(0.00405)
Log(Lagged Size)		-0.146***	0.00431	
		(0.00235)	(0.00311)	
Year–Month FE	Yes	Yes	Yes	Yes
Size Category FE	No	No	No	Yes
R-squared	0.442	0.328	0.442	0.445
Observations	3,254,302	3,254,302	3,254,302	3,254,302

Panel B: Time Series

	Log(Total Volatility)			
	(1)	(2)	(3)	(4)
Log(Lagged Price)	-0.260***		-0.261***	-0.274***
	(0.00395)		(0.00477)	(0.00403)
Log(Lagged Size)		-0.160***	0.000476	
		(0.00334)	(0.00383)	
Stock FE	Yes	Yes	Yes	Yes
Year–Month FE	Yes	Yes	Yes	Yes
Size Category FE	No	No	No	Yes
R-squared	0.588	0.565	0.588	0.588
Observations	3,254,302	3,254,302	3,254,302	3,254,302

Table 3

Baseline Results: Idiosyncratic Volatility and Market Beta

This table repeats the analysis of Table 2, Panel A, using idiosyncratic volatility and absolute market beta as the outcome variable. Variables are as defined in Table 1 and 2. Standard errors are double-clustered by stock and year-month. *,**, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Panel A: Idiosyncratic Volatility

	Log(Idiosyncratic Volatility)			
	(1)	(2)	(3)	(4)
Log(Lagged Price)	-0.360***		-0.332***	-0.346***
	(0.00320)		(0.00434)	(0.00399)
Log(Lagged Size)		-0.173***	-0.0224***	
		(0.00217)	(0.00308)	
Year–Month FE	Yes	Yes	Yes	Yes
Size Category FE	No	No	No	Yes
R-squared	0.469	0.363	0.470	0.473
Observations	3,254,302	3,254,302	3,254,302	3,254,302

Panel B: Market Beta

	Log(|Beta|)			
	(1)	(2)	(3)	(4)
Log(Lagged Price)	-0.228***		-0.325***	-0.319***
	(0.00395)		(0.00521)	(0.00465)
Log(Lagged Size)		-0.0717***	0.0757***	
		(0.00276)	(0.00375)	
Year–Month FE	Yes	Yes	Yes	Yes
Size Category FE	No	No	No	Yes
R-squared	0.097	0.068	0.102	0.103
Observations	3,254,302	3,254,302	3,254,302	3,254,302

Table 4
The Leverage Effect Puzzle: Past Returns versus Price

Panel A of this table repeats the analysis of Table 2, Panel A, controlling for a stock's return in the 12 months leading up to month t. The sample is limited to observations where the dependent variable and independent variables in all columns are non-missing. In column 4 we control separately for past returns in each the previous 12 months. Panel B restricts the sample to firms with zero book leverage (according to COMPUSTAT data) in the quarter before month t. Variables are as defined in Tables 1 and 2. Standard errors are double-clustered by stock and year-month. *,**, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Panel A: Full Sample

	Log(Total Volatility)			
	(1)	(2)	(3)	(4)
Log(Lagged Price)	-0.339***		-0.332***	-0.331***
	(0.00412)		(0.00465)	(0.00466)
Log(1+Past 12-Month Return)		-0.240***	-0.0309***	
		(0.0101)	(0.00902)	
Year–Month FE	Yes	Yes	Yes	Yes
Size Category FE	Yes	Yes	Yes	Yes
Past 12 Monthly Returns	No	No	No	Yes
R-squared	0.458	0.346	0.458	0.459
Observations	2,966,196	2,966,196	2,966,196	2,966,196

Panel B: Zero Leverage Subsample

	Log(Total Volatility)			
	(1)	(2)	(3)	(4)
Log(Lagged Price)	-0.288***		-0.286***	-0.285***
	(0.00800)		(0.00851)	(0.00855)
Log(1+Past 12-Month Return)		-0.160***	-0.00970	
		(0.0139)	(0.0122)	
Year–Month FE	Yes	Yes	Yes	Yes
Size Category FE	Yes	Yes	Yes	Yes
Past 12 Monthly Returns	No	No	No	Yes
R-squared	0.357	0.246	0.357	0.358
Observations	201,509	201,509	201,509	201,509

Table 5
Additional Controls

This table repeats the analysis of Table 2, Panel A, including additional controls. The sample is limited to observations where the dependent variable and independent variables in all columns are non-missing. Other variables are as defined in Tables 1 and 2. Some of the variables only change on a quarterly basis. Standard errors are double-clustered by stock and year-month. *,**, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	Log(Total Volatility)					
	(1)	(2)	(3)	(4)	(5)	(6)
Log(Lagged Price)	-0.306***	-0.308***	-0.285***	-0.282***	-0.280***	-0.281***
	(0.00526)	(0.00655)	(0.00629)	(0.00625)	(0.00624)	(0.00639)
Log(Lagged Sales Volatility)			0.0606***	0.0477***	0.0430***	0.0429***
			(0.00227)	(0.00182)	(0.00197)	(0.00196)
Lagged Market-to-Book				0.0378***	0.0351***	0.0349***
				(0.00199)	(0.00192)	(0.00190)
Lagged Volume Turnover					0.0259***	0.0258***
					(0.00545)	(0.00544)
Lagged Bid-Ask Spread Percentage					0.000294	0.000295
					(0.000190)	(0.000191)
Lagged Leverage						-0.0301***
						(0.0107)
Log(Lagged Size)	No	Yes	Yes	Yes	Yes	Yes
Size Category FE	No	Yes	Yes	Yes	Yes	Yes
Log(Lagged Size) × Size Category FE	No	Yes	Yes	Yes	Yes	Yes
Year–Month FE	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.426	0.431	0.443	0.456	0.467	0.467
Observations	1,209,015	1,209,015	1,209,015	1,209,015	1,209,015	1,209,015

Table 6
Alternative Volatility Measures

This table repeats the analysis of Table 2, Panel A, but uses alternative linear measures of return volatility that are robust to tick size distortions (Hau, 2006). In column (1), volatility is measured as the mean intraday price range percentage ($100 \times \frac{High-Low}{High}$) over all trading days in a stock-month. In column (2), volatility is measured as the mean absolute deviation ($|Ret - \overline{Ret}|$) over all trading days in stock-month. In column (3), volatility is measured as the mean absolute return ($|Ret|$) over all trading days in a stock-month. Standard errors are double-clustered by stock and year-month. *,**, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	Log(Volatility Measure)		
	(1) Intraday Range	(2) Absolute Deviation	(3) Absolute Return
Log(Lagged Price)	-0.410***	-0.325***	-0.312***
	(0.00513)	(0.00472)	(0.00542)
Year–Month FE	Yes	Yes	Yes
Size Category FE	Yes	Yes	Yes
R-squared	0.507	0.397	0.353
Observations	2,555,207	3,254,302	3,254,302

Table 7
Institutional Ownership

This table repeats the analysis of Table 2 Panel A, with the addition of institutional ownership as a control variable, as well as institutional ownership interacted with price. Institutional ownership is computed as defined in Table 1, and is updated quarterly. Standard errors are double-clustered by stock and year-month. *,**, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	(1) Log(Total Volatility)	(2) Log(Idios. Vol.)	(3) Log(|Beta|)
Log(Lagged Price)	-0.384***	-0.381***	-0.393***
	(0.00509)	(0.00511)	(0.00582)
Log(Lagged Price) $\times$ Lagged Inst. Own.	0.169***	0.137***	0.174***
	(0.0108)	(0.0107)	(0.0128)
Lagged Inst. Own.	-0.311***	-0.279***	-0.126***
	(0.0323)	(0.0315)	(0.0405)
Year–Month FE	Yes	Yes	Yes
Size Category FE	Yes	Yes	Yes
R-squared	0.432	0.462	0.112
Observations	2,113,118	2,113,118	2,113,118

Table 8

Response to News Events Identified Through Textual Analysis

This table shows the relation between the return response to a news event and the nominal price of a stock prior to the event. Cumulative abnormal returns (CAR) are computed from trading day -1 to day +1 relative to the event. Benchmark returns during the event window are based on the market model. Market betas are estimated based on returns in days -150 to -100 relative to the event date. Lagged Price is the price of the stock on trading day -2. News events come from Boudoukh et al. (2018). The first two columns limit the sample to categorized firm-specific news events, which are events that Boudoukh et al. (2018) are able to categorize using an algorithm. The final two columns limit the sample to non-categorized news events, which are events that Boudoukh et al. (2018) are not able to categorize. Other variables are as defined in Table 1 and 2. Standard errors are double-clustered by stock and year-month. *,**, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	Log(|CAR|)			
	Categorized News		Other News	
	(1)	(2)	(3)	(4)
Log(Lagged Price)	-0.299***	-0.217***	-0.279***	-0.208***
	(0.0161)	(0.0161)	(0.0156)	(0.0169)
Year–Month FE	Yes	Yes	Yes	Yes
Size Category FE	No	Yes	No	Yes
R-squared	0.105	0.115	0.106	0.111
Observations	377,454	377,454	375,123	375,123

Table 9

Response to Earnings Announcements

Panel A of this table shows the relation between the return response to an earnings announcement and the nominal price of a stock prior to the announcement. Cumulative abnormal returns (CAR) are computed from trading day -1 to day +1 relative to the announcement. Benchmark returns during the event window are based on the market model. Market betas are estimated based on returns in days -150 to -100 relative to the announcement date. The variable Lagged Price is the price of the stock on trading day -2. Analyst count fixed effects are fixed effects for the number of analysts that made an earnings forecast prior to the announcement. Panel B examines how the return response to earnings news varies with a stock's pre-announcement nominal price level. Observations are at the announcement level. SUE Decile Rank is the decile of standardized unexpected earnings. Standardized unexpected earnings are defined as the difference between announced earnings and mean analyst expectations, divided by the standard deviation of analyst expectations. To avoid using stale information in our measure of analyst expectations, analyst's forecasts that are made more than 60 days prior to the announcement are excluded. CAR represents the cumulative abnormal return around the earning announcement. Abnormal returns are computed relative to the market model, where market betas are estimated based on returns from dates $t-150$ to $t-50$. In columns 1–3, CAR is computed from the day before the announcement to the day after. In columns 4–6, CAR is computed from 10 days before the announcement to 20 days after. $Log(\ddot{Price}_{i,t-2})$ represents the demeaned log price prior to the earnings announcement, and $log(\ddot{Size}_{i,t-2})$ represents the demeaned log size prior to the earnings announcement. Standard errors are double-clustered by stock and year-month. *,**, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Panel A: Return Response on Earnings Announcement Days

	Log(|CAR|)			
	(1)	(2)	(3)	(4)
Log(Lagged Price)	-0.223***	-0.232***	-0.271***	-0.210***
	(0.00747)	(0.0102)	(0.00791)	(0.00944)
Year–Month FE	Yes	Yes	Yes	Yes
Size Category FE	No	Yes	No	Yes
Analyst Count FE	No	No	Yes	Yes
R-squared	0.067	0.071	0.072	0.082
Observations	339,736	339,736	339,736	339,736

Table 9
(Continued)

Panel B: Return Response to Earnings Surprises

	$\text{Log}(1 + \text{CAR}_{[t-1,t+1]})$			$\text{Log}(1 + \text{CAR}_{[t-10,t+20]})$		
	(1)	(2)	(3)	(4)	(5)	(6)
SUE Decile Rank	0.00741***	0.00732***	0.00741***	0.0109***	0.0110***	0.0108***
	(0.000180)	(0.000196)	(0.000181)	(0.000296)	(0.000319)	(0.000305)
$\text{Log}(\ddot{\text{Price}}_{t-2})$	0.0104***		0.0100***	0.0308***		0.0267***
	(0.00119)		(0.00161)	(0.00392)		(0.00481)
SUE Decile Rank $\times \text{Log}(\ddot{\text{Price}}_{t-2})$	-0.00223***		-0.00220***	-0.00371***		-0.00293***
	(0.000205)		(0.000286)	(0.000472)		(0.000634)
Log(Lagged Size)		0.00375***	0.000242		0.0128***	0.00306*
		(0.000463)	(0.000603)		(0.00154)	(0.00156)
SUE Decile Rank $\times \text{Log}(\ddot{\text{Size}}_{t-2})$		-0.000758***	-0.0000233		-0.00164***	-0.000567***
		(0.0000683)	(0.0000946)		(0.000166)	(0.000209)
Year–Month FE	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.082	0.080	0.082	0.080	0.078	0.080
Observations	89,279	89,279	89,279	89,156	89,156	89,156

Table 10
Nominal Prices and Post Earnings Announcement Drift

This table examines how the strength of post-earnings-announcement drift varies with a stock's pre-announcement nominal price level. Observations are at the announcement level. The sample is the same as in Panel B of Table 9. The variable $CAR_{[t+2,\tau]}$ represents drift, i.e., cumulative abnormal returns following the announcement from date $t+2$ to date $\tau \in \{10, 20, ..., 60\}$, $CAR_{[t-1,t+1]}$ represents the initial return response to the earnings announcement from date $t-1$ to date $t+1$, $log(\ddot{Price}_{i,t-2})$ represents the demeaned log price prior to the earnings announcement, and $log(\ddot{Size}_{i,t-2})$ represents the demeaned log size prior to the earnings announcement. Abnormal returns are computed relative to the market model, where market betas are estimated based on returns from dates $t-150$ to $t-50$. Standard errors are double-clustered by stock and year-month. *,**, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	$\text{Log}(1+\text{CAR}_{[t+2,\tau]})$					
	(1) $\tau = 10$	(2) $\tau = 20$	(3) $\tau = 30$	(4) $\tau = 40$	(5) $\tau = 50$	(6) $\tau = 60$
$\text{Log}(1+\text{CAR}_{[t-1,t+1]})$	0.00632	0.0175*	0.0316**	0.0551***	0.0701***	0.0795***
	(0.00920)	(0.0104)	(0.0134)	(0.0170)	(0.0183)	(0.0215)
$\text{Log}(\ddot{\text{Price}}_{t-2})$	-0.0000384	-0.000683	0.000866	0.00275	0.00390	0.00426
	(0.00130)	(0.00197)	(0.00243)	(0.00288)	(0.00334)	(0.00375)
$\text{Log}(1+\text{CAR}_{[t-1,t+1]}) \times \text{Log}(\ddot{\text{Price}}_{t-2})$	0.00521	0.0130	0.0286*	0.0668***	0.0959***	0.0866***
	(0.0106)	(0.0142)	(0.0169)	(0.0235)	(0.0238)	(0.0251)
$\text{Log}(\ddot{\text{Size}}_{t-2})$	0.000336	0.000677	0.000107	-0.0000439	0.000161	0.00122
	(0.000368)	(0.000595)	(0.000820)	(0.00100)	(0.00113)	(0.00135)
$\text{Log}(1+\text{CAR}_{[t-1,t+1]}) \times \text{Log}(\ddot{\text{Size}}_{t-2})$	0.00711	0.00663	-0.00653	-0.0221*	-0.0311***	-0.0419***
	(0.00577)	(0.00791)	(0.00987)	(0.0126)	(0.0115)	(0.0137)
Year–Month FE	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.030	0.038	0.045	0.045	0.051	0.054
Observations	88,020	88,020	88,020	88,020	88,020	88,020

Table 11

Return Reversal, Variation by Lagged Price and Size

This table shows results from regressions of future abnormal returns on past abnormal returns and the interaction between past abnormal returns and lagged price and size. Abnormal returns are measured using market-adjusted returns as in De Bondt and Thaler (1985). The regression also controls for the direct effects of lagged price and size. All regressions are estimated following the Fama-MacBeth methodology. Columns 1–3 focus on long-run reversal. The sorting period is $t-36$ to $t-1$. Lagged price and size are measured as of the end of month $t-37$ (which precedes the past return window covering months $t-36$ to $t-1$). Columns 4–6 focus on short-run reversal. The sorting period is month $t-1$. Lagged price and size are measured as of the end of month $t-2$ (which precedes the past return window covering month $t-1$). Standard errors reflect the Fama-Macbeth methodology. *,**, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	Log(1 + 36 Month CAR)			Log(1 + 1 Month CAR)		
	(1)	(2)	(3)	(4)	(5)	(6)
Log(1 + Prev 36 Month CAR)	-0.154***	-0.186***	-0.158***			
	(0.00598)	(0.00982)	(0.00984)			
Log(1 + Prev 36 Month CAR) × Log(Price_{t-37})	0.0311***		0.0314***			
	(0.00183)		(0.00216)			
Log(1 + Prev 36 Month CAR) × Log(Size_{t-37})		0.0112***	0.000188			
		(0.00106)	(0.00124)			
Log(1 + Prev 1 Month CAR)				-0.124***	-0.205***	-0.152***
				(0.00579)	(0.0108)	(0.0110)
Log(1 + Prev 1 Month CAR) × Log(Price_{t-2})				0.0284***		0.0238***
				(0.00187)		(0.00226)
Log(1 + Prev 1 Month CAR) × Log(Size_{t-2})					0.0156***	0.00409***
					(0.00114)	(0.00136)
Fama-MacBeth	Yes	Yes	Yes	Yes	Yes	Yes
Avg R-squared	0.073	0.069	0.084	0.048	0.039	0.056
Observations	1,717,530	1,717,530	1,717,530	3,256,589	3,256,589	3,256,589
Time Periods	1,014	1,014	1,014	1,084	1,084	1,084

INTERNET APPENDIX

A Supplemental Exhibits

Figure A1
Volatility around Reverse Splits

This figure repeats the analysis of Figure 6 (Panel A) for reverse splits.

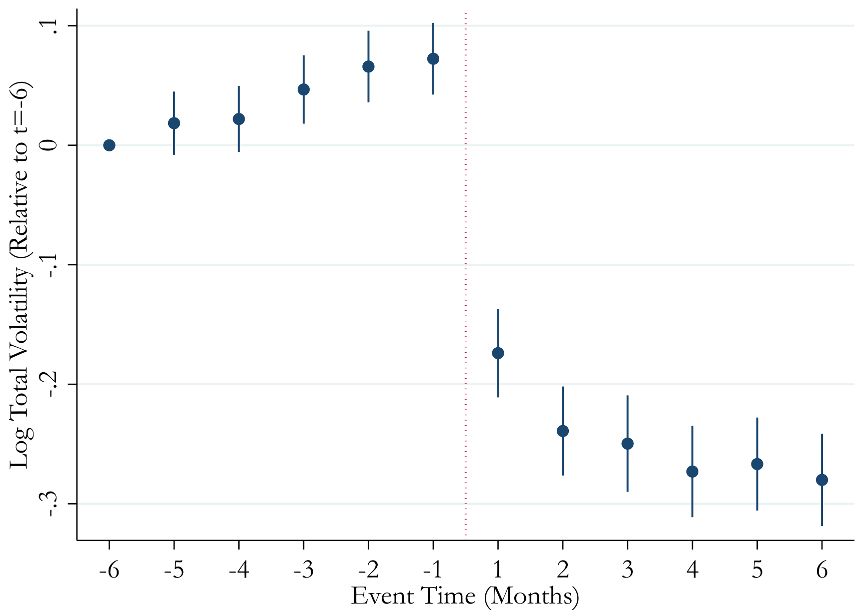


Figure A2
Volatility and Beta Around Stock Splits with Controls

This figure repeats the analysis of Figure 6 (Panel A), including controls for volume turnover and bid-ask spread percentage.

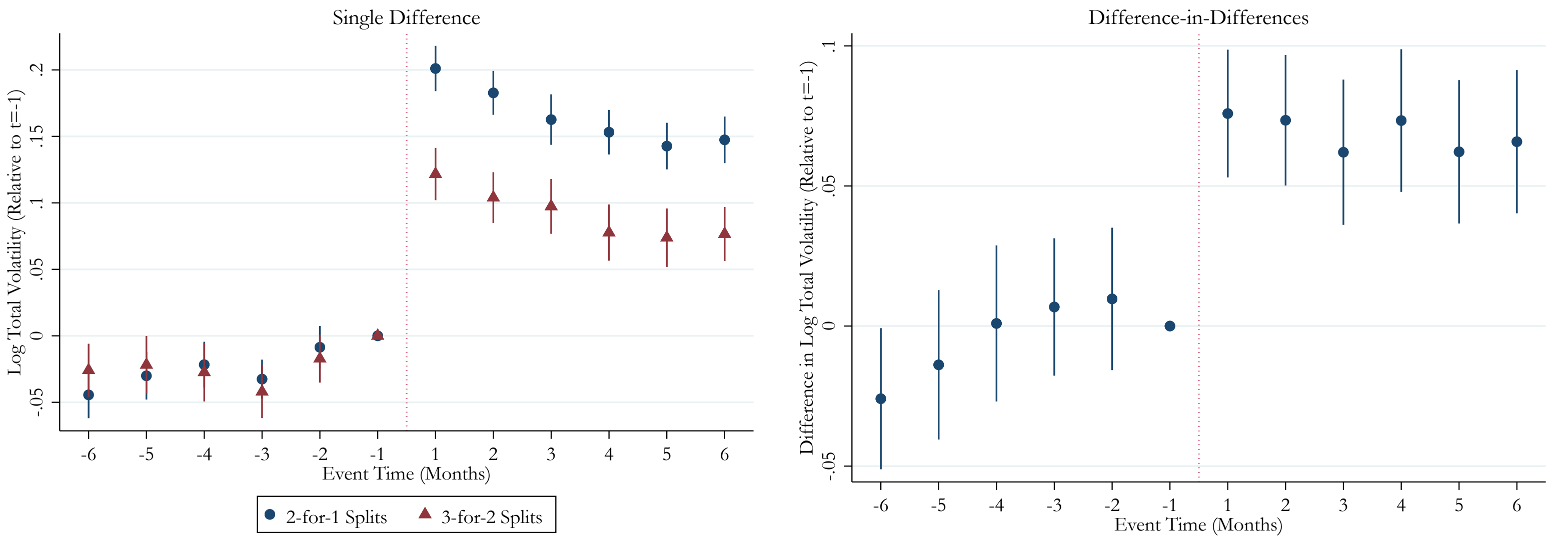


Figure A3

Regression Discontinuity: Intraday Price Range Around Stock Splits—Large Cap Subsample

This figure repeats the analysis of Figure 5 restricting the sample to firms in Fama French size categories 11 to 20 as of the month prior to the split.

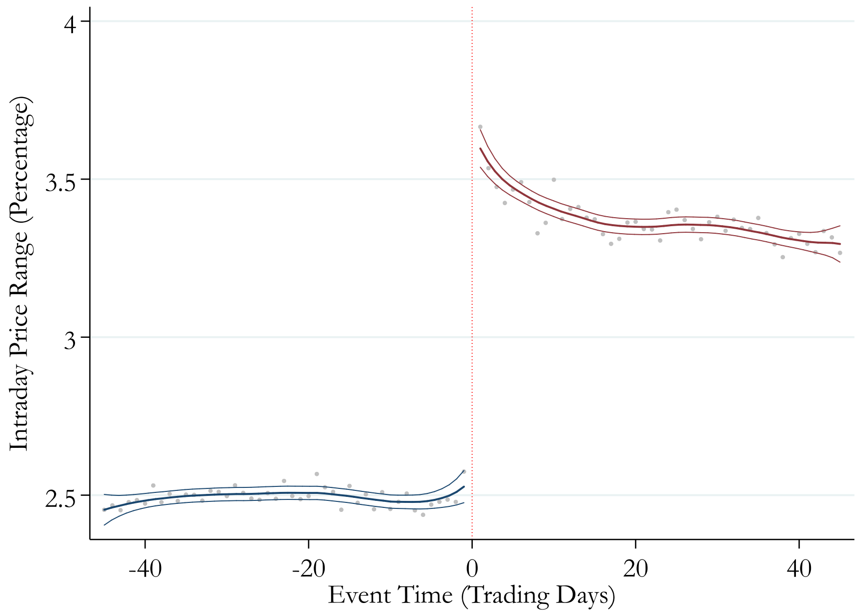


Figure A4

Event Study: Volatility Around Stock Splits—Large Cap Subsample

This figure repeats the analysis of Figure 6 (Panel A), restricting the sample to stocks in Fama French size categories 11 to 20 as of the month prior to the split.

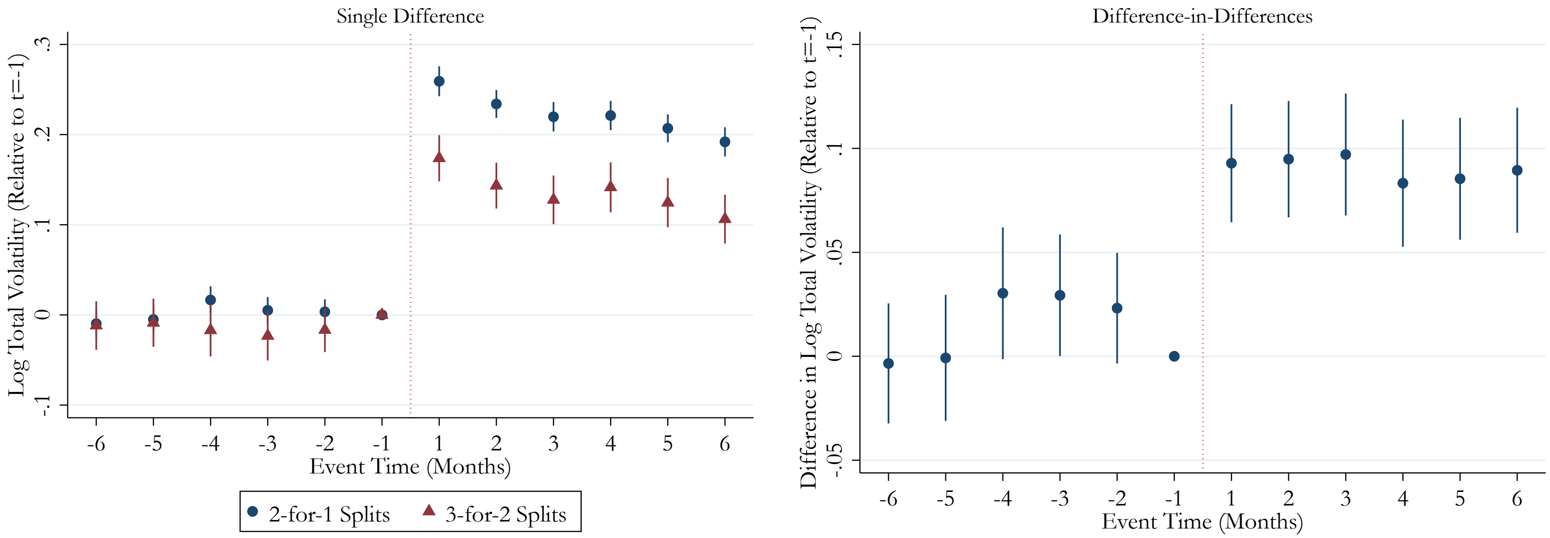


Figure A5

Regression Discontinuity: Volume Turnover Around Splits

This figure repeats the analysis of Figure 5 using volume turnover rather than intraday price range percentage.

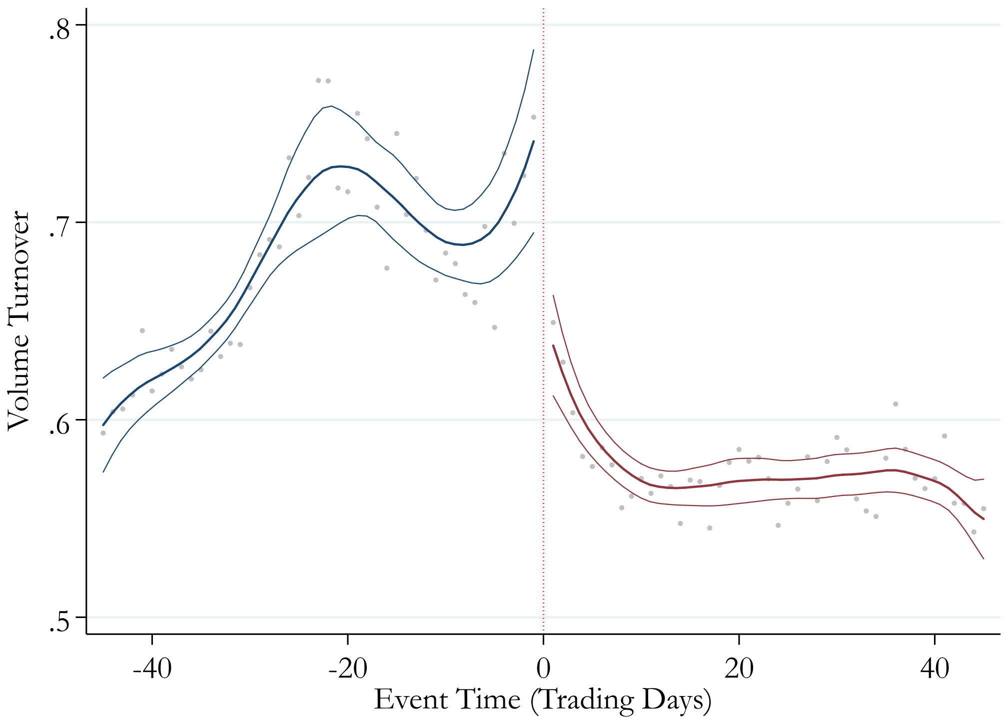


Figure A6
Intraday Extreme Absolute Return

This figure repeats the analysis of Figure 5 using intraday extreme absolute returns. This is defined as $100 \times max\{|\frac{High-PrevClose}{PrevClose}|, |\frac{Low-PrevClose}{PrevClose}|\}$, where $High$ is the intraday high, Low is the intraday low, and $PrevClose$ is the previous trading day's closing price.

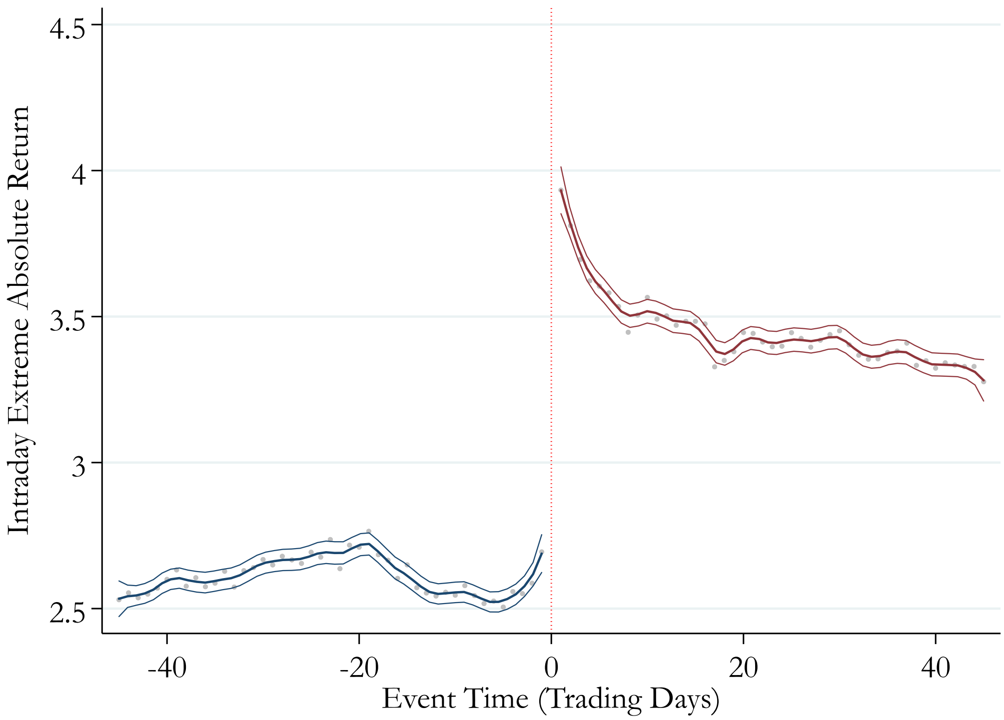


Table A1
Baseline Results: Market Beta—Positive Only

This table repeats the analysis of Table 3, Panel B, limiting the sample to observations with positive estimated market betas. Standard errors are double-clustered by stock and year-month. *,**, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	Log(Beta)			
	(1)	(2)	(3)	(4)
Log(Lagged Price)	-0.202***		-0.297***	-0.296***
	(0.00369)		(0.00550)	(0.00493)
Log(Lagged Size)		-0.0592***	0.0720***	
		(0.00244)	(0.00375)	
Year–Month FE	Yes	Yes	Yes	Yes
Size Category FE	No	No	No	Yes
R-squared	0.090	0.064	0.095	0.097
Observations	2,315,198	2,315,198	2,315,198	2,315,198

Table A2

Baseline Results: Controlling for Shares Outstanding

This table repeats the cross-sectional analysis of Tables 2 and 3 replacing the control for log(lagged size) with a control for log(lagged shares outstanding). Standard errors are double-clustered by stock and year-month. *,**, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	Log(Total Volatility)		Log(Idiosyncratic Volatility)		Log(|Beta|)	
	(1)	(2)	(3)	(4)	(5)	(6)
Log(Lagged Price)	-0.326***	-0.327***	-0.360***	-0.354***	-0.228***	-0.250***
	(0.00339)	(0.00327)	(0.00320)	(0.00301)	(0.00395)	(0.00380)
Log(Lagged Shares Outstanding)		0.00431		-0.0224***		0.0757***
		(0.00311)		(0.00308)		(0.00375)
Year–Month FE	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.442	0.442	0.469	0.470	0.097	0.102
Observations	3,254,302	3,254,302	3,254,302	3,254,302	3,254,302	3,254,302

Table A3

Robustness to Flexible Size Controls

This table tests for the robustness of the baseline results to the addition of more flexible controls for size. It repeats the analysis of Table 2 with additional size controls. In column 1 of Panel A, 100 size category indicator variables are included in the regression. In column 2, those 100 indicator variables are allowed to interact with year-month fixed effects, thus allowing the size-volatility relation to vary each month. In columns 3–4, size is further controlled for continuously within each bin. In column 3, size is controlled for linearly within each bin, in column 4 size is controlled for logarithmically within each bin. In Panel B, the same exercise is repeated with 500 size bins. Standard errors are double-clustered by stock and year-month. *,**, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Panel A: 100 Size Categories

	Log(Total Volatility)			
	(1)	(2)	(3)	(4)
Log(Lagged Price)	-0.336***	-0.354***	-0.355***	-0.355***
	(0.00428)	(0.00438)	(0.00446)	(0.00445)
Year–Month FE	Yes	No	No	No
Size Cat. FE	Yes	No	No	No
Year–Month FE × Size Cat. FE	No	Yes	Yes	Yes
Year–Month FE × Size Cat. FE × Lagged Market Cap	No	No	Yes	No
Year–Month FE × Size Cat. FE × Log(Lagged Market Cap)	No	No	No	Yes
R^2	0.445	0.486	0.501	0.501
Observations	3,254,302	3,254,302	3,254,302	3,254,302

Panel B: 500 Size Categories

	Log(Total Volatility)			
	(1)	(2)	(3)	(4)
Log(Lagged Price)	-0.336***	-0.358***	-0.363***	-0.363***
	(0.00428)	(0.00440)	(0.00479)	(0.00477)
Year–Month FE	Yes	No	No	No
Size Cat. FE	Yes	No	No	No
Year–Month FE × Size Cat. FE	No	Yes	Yes	Yes
Year–Month FE × Size Cat. FE × Lagged Market Cap	No	No	Yes	No
Year–Month FE × Size Cat. FE × Log(Lagged Market Cap)	No	No	No	Yes
R^2	0.445	0.534	0.601	0.600
Observations	3,254,302	3,254,302	3,254,302	3,254,302

Table A4

Time Period Subsamples

This table repeats the analysis of Table 2 Panel A, on subsamples from each decade from the 1920s through the 2010s. The sample ends in 2016, so column 10 corresponds to the years 2010-2016 only. Standard errors are double-clustered by stock and year-month. *,**, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	Log(Total Volatility)									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	1920s	1930s	1940s	1950s	1960s	1970s	1980s	1990s	2000s	2010s
Log(Lagged Price)	-0.227***	-0.275***	-0.350***	-0.191***	-0.324***	-0.462***	-0.317***	-0.369***	-0.353***	-0.251***
	(0.0140)	(0.0108)	(0.00989)	(0.0147)	(0.0126)	(0.00862)	(0.00646)	(0.00768)	(0.00995)	(0.00554)
Year–Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Size Category FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.560	0.652	0.609	0.289	0.396	0.353	0.315	0.440	0.449	0.356
Observations	22,843	82,661	97,620	118,906	209,217	452,864	624,639	751,051	586,932	307,569

Table A5

Size Subsamples

This table repeats the analysis of Table 2, Panel A, on 20 subsamples corresponding to 20 different size categories based on market capitalization (prc×shrout). Size1 corresponds to the smallest size category, and Size20 the largest. The size categories are based on the monthly ME Breakpoints from Ken French's data library. The breakpoints for a given month use all NYSE stocks that have a CRSP share code of 10 or 11 and have good shares and price data, excluding closed-end funds and REITs. There are 20 groups corresponding to every fifth percentile. Observations in our data are not equally distributed across the categories, because our sample includes all stocks on NYSE, AMEX, and NASDAQ with a share code of 10 or 11, rather than only NYSE. Standard errors are double-clustered by stock and year-month. *,**, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	Log(Total Volatility)									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Size1	Size2	Size3	Size4	Size5	Size6	Size7	Size8	Size9	Size10
Log(Lagged Price)	-0.363***	-0.386***	-0.370***	-0.364***	-0.346***	-0.325***	-0.310***	-0.298***	-0.281***	-0.270***
	(0.00562)	(0.00659)	(0.00746)	(0.00771)	(0.00800)	(0.00816)	(0.00870)	(0.00870)	(0.00949)	(0.00996)
Year–Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.393	0.368	0.363	0.362	0.354	0.349	0.347	0.351	0.343	0.350
Observations	1,111,769	333,979	226,006	173,581	146,796	128,577	117,145	107,699	99,812	92,354

	Log(Total Volatility)									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Size11	Size12	Size13	Size14	Size15	Size16	Size17	Size18	Size19	Size20
Log(Lagged Price)	-0.248***	-0.227***	-0.207***	-0.201***	-0.184***	-0.168***	-0.166***	-0.124***	-0.123***	-0.139***
	(0.00969)	(0.0103)	(0.0118)	(0.0123)	(0.0135)	(0.0139)	(0.0179)	(0.0165)	(0.0206)	(0.0215)
Year–Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.355	0.359	0.351	0.357	0.359	0.388	0.403	0.412	0.450	0.526
Observations	85,267	81,440	78,053	75,213	72,894	70,567	67,662	65,314	62,743	57,431

Table A6

Upside and Downside Volatility

This table repeats the analysis of Table 2, Panel A, Column 4, with modifications to the dependent variable to explore the relation between lagged price and measures of upside and downside volatility. Column 1 measures volatility as the log of the annualized square root of mean squared daily returns within each month. Columns 2 and 3 use a similar annualized volatility measure but calculated using only daily returns that are positive or negative, respectively. Thus, Columns 2 and 3 use measures of upside and downside volatility, respectively. Column 4 uses the log of the absolute market beta (calculated using daily returns within each month, estimated with a Dimson (1979) correction), while Columns 5 and 6 use the log of the absolute beta calculated only on days in which the market return was positive or negative, respectively. Thus, Columns 5 and 6 use measures of upside and downside beta, respectively. Standard errors are double-clustered by stock and year-month. *,**, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	Log(Mean Squared Returns)			Log(|Beta|)		
	(1)	(2)	(3)	(4)	(5)	(6)
	All	$Ret_i > 0$	$Ret_i < 0$	All	$Ret_{mkt} > 0$	$Ret_{mkt} < 0$
Log(Lagged Price)	-0.337***	-0.397***	-0.365***	-0.319***	-0.341***	-0.336***
	(0.00401)	(0.00374)	(0.00372)	(0.00465)	(0.00389)	(0.00410)
Year–Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Size Category FE	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.444	0.521	0.543	0.103	0.180	0.217
Observations	3,254,302	3,209,814	3,220,782	3,254,302	3,254,302	3,254,302

Table A7

Regression Discontinuity: Intraday Price Range Around Stock Splits

This table explores the pattern of volatility around 2-for-1 stock splits. We examine 45 days before and after the split. Variables are as defined in Table 1. Control functions on each side of the cutoff are estimated non-parametrically using local linear regression. The first three columns use a triangular kernel. The last three columns use a rectangular kernel. Bandwidths are selected using one common MSE-optimal bandwidth selector in columns (1) and (4). Other bandwidths are shown in the remaining columns. The estimated coefficient represents the size of the discontinuity at the split date, as illustrated in Figure 5.

	Intraday Price Range (Percentage)					
	(1)	(2)	(3)	(4)	(5)	(6)
Discontinuity at Split Date	1.361***	1.377***	1.374***	1.368***	1.350***	1.352***
	(0.0475)	(0.0678)	(0.0408)	(0.0437)	(0.0545)	(0.0352)
Degree Local Poly	1	1	1	1	1	1
Bandwidth	7.933	5	10	7.933	5	10
Kernel	Triangular	Triangular	Triangular	Uniform	Uniform	Uniform
Observations	573,778	573,778	573,778	573,778	573,778	573,778

Table A8
Volatility and Liquidity Around Stock Splits

This table explores whether changes in liquidity after 2-for-1 splits can explain changes in volatility. The sample is restricted to the subsample of stocks for which bid-ask spread and volume turnover data are available. Volume turnover and bid-ask spread percentage are as defined in Table 1. Standard errors are double-clustered by stock and year-month. *,**, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	Log(Volatility)	
	(1)	(2)
Post Split	0.200***	0.196***
	(0.00604)	(0.00524)
Volume Turn.		2.576***
		(0.0565)
B-A Spread		0.0820***
		(0.00450)
Year–Month FE	Yes	Yes
Stock FE	Yes	Yes
R-squared	0.684	0.734
Observations	40,121	40,121

Table A9
Stock Characteristics Around Splits

This table shows mean institutional ownership and sales volatility before and after 2-for-1 stock splits, as well as the difference. Variables are as defined in Tables 1 and 2. Before (after) split institutional ownership refers to institutional ownership based on the last (first) observed 13f filing for each stock prior to (following) the split. Before (after) split sales volatility refers to sales volatility based on the most last (first) four completed quarters prior to (following) the split.

	Before Split			After Split			Difference		
	Obs	Mean	Std Dev	Obs	Mean	Std Dev	Obs	Mean	Std Dev
Inst. Ownership	4,075	0.481	0.286	4,138	0.471	0.276	8,213	0.010	0.006
Sales Volatility	4,042	0.203	1.646	4,215	0.192	1.585	8,257	0.011	0.036

B Option-Implied Volatility and a Trading Strategy

In this section, we explore the extent to which option traders anticipate the change in volatility following splits and how quickly they update their beliefs about volatility after the split. If option traders are very sophisticated, we expect that implied volatility (which reflects option traders' expectations of volatility over some future period) should increase prior to a split execution date, as splits are announced in advance, typically by one month. While many of the splits in our sample either pre-date the OptionMetrics data or are associated with stocks with few traded options, we are able to obtain option data for 921 split events. Panel A of Figure B1 plots 30-day implied volatility and 30-day realized volatility around splits.[26] Implied volatility is calculated as a linear combination of implied volatilities from call options with approximate 30-day maturities, and realized volatility represents the realized volatility over the *same* subsequent 30-day window. In unreported results, we find similar results using implied volatility estimated from data on put options. The figure shows that option traders partially anticipate an increase in volatility but undershoot by a substantial margin. After the split, the 30-day implied volatility remains below the 30-day realized volatility, and does not converge until approximately 100 trading days after the split execution date. This shows that option traders do not fully anticipate the change in volatility around splits, and they do not immediately change their beliefs after the split.

The difference in implied volatility and realized volatility following split events suggests a profitable trading strategy that would involve going long option straddles (equivalent to buying both a call and put option) prior to pre-announced split execution dates. Option straddles pay off when realized volatility exceeds implied volatility, which is what we observe in the data following stock splits. Panel B of Figure B1 plots the returns to a straddle trading strategy. Details of the trading strategy are described in the figure notes. We find that this simple strategy of going long straddles around split execution dates leads to an average 15 percent return (not annualized) over the subsequent 40 trading days.

[26]The figure displays a cyclical pattern that repeats approximately every three months. We believe this pattern is driven by quarterly earnings announcements, which cause an increase in volatility and implied volatility. Splits are often pre-announced around the time of the earnings announcement and executed one month later. The figure also shows that, on average, implied volatility exceeds realized volatility. This is a general feature of options data and may be explained by investors demanding compensation for risk.

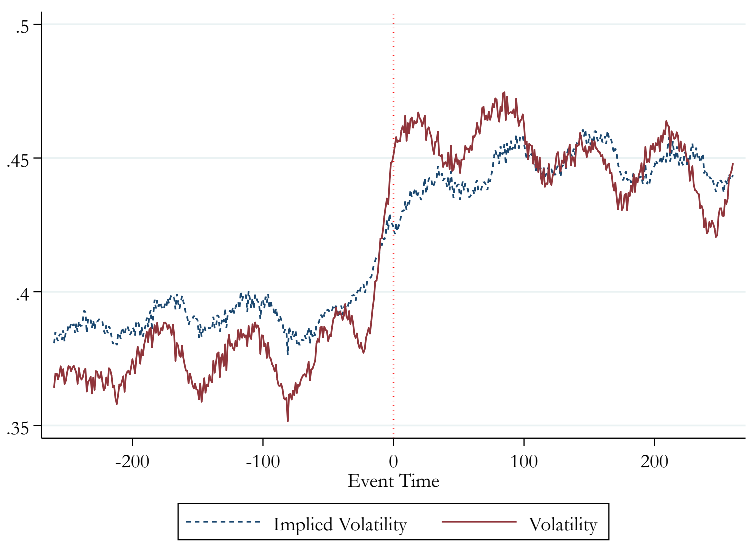
Because OptionMetrics data is only available for larger and more liquid stocks, these results also show that our findings related to splits are not a small-cap phenomenon. Even for large-cap stocks with options data, realized volatility jumps up significantly around splits, and implied volatility also increases, albeit with a lag consistent with option traders reacting with a delay.

Figure B1

Option-Implied Volatility Around Splits and Trading Strategy

Panel A of this figure plots implied volatility and realized volatility around stock splits. Implied volatility is calculated by OptionMetrics as a linear combination of implied volatilities from call options with approximately 30-day maturities. Realized volatility represents the realized volatility over the matching subsequent 30-day period. The sample is limited to 2-for-1 stock splits or greater, and includes 921 firm-split events from 1995-2015 where data are available from OptionMetrics. Panel B plots the returns to a straddle trading strategy. We identify all call and put options on a given stock of matching time-to-maturities that satisfy basic filtering criteria. These filters are: (1) the option prices are at least \$0.125; (2) the underlying stock prices are at least \$5; (3) options have positive open interest; (4) basic no arbitrage bounds, e.g., (bid>0, bid <offer, strike price≥bid and offer≥max(0, strike price − stock price) for put options; (5) time to maturities between 10 to 60 days; and (6) at the time of straddle formation, options must have an absolute delta between 0.375 and 0.625. For each pair of puts and calls with matching maturities and strike prices, we construct a delta-neutral straddle. A delta-neutral straddle involves purchasing a put and a call; the weights of the put and call in the portfolio are given by -(δ_p)/(δ_c-δ_p) and (δ_c)/(δ_c-δ_p), respectively, where δ_c and δ_p are the delta of the call and put option, respectively. For splits with multiple straddles available, we weight each straddle using the minimum open interest of the call or put side of the straddle. For each split event, we construct the straddle portfolio on the split execution date (and reconstruct it every fifth day for the next 35 days) and measure the returns to holding the portfolio for five days, using the median of end-of-day bid and ask quotes to construct returns. There are 819 split events in this sample. The figure plots the average daily compounded return of the straddle strategy, with vertical lines representing 95% confidence intervals.

Panel A: Implied and Realized Volatility



Panel B: Straddle Trading Strategy Return