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The Market Reaction to Stock Splits

CHRISTOPHER G. LAMOUREUX and PERCY POON*

ABSTRACT

In this paper, a model of market reaction to stock splits is presented and tested. We argue that the announcement of a split sets off the following chain of events. The market recognizes that, subsequent to the (reverse) split ex-day, the daily number of transactions along with the raw volume of shares traded will increase (decrease). This increase in volume results in an increase in the noisiness of the security's return process. The increase in noise raises the tax-option value of the stock, and it is this value that generates the announcement effect of stock splits. Empirical evidence using security returns, daily trading volume, and shareholder data strongly supports this theory. The evidence, in conjunction with this theory, also agrees with extant literature that splits result in decreased liquidity, but there is no evidence that this reduction in liquidity is priced.

STOCK SPLITS HAVE PRESENTED finance theorists with a conundrum. These "nonevents" seem to be a purely cosmetic change; nevertheless, research shows that significant price reaction is attributable directly to splits. Recently, Grinblatt, Masulis, and Titman [12] show that, even in "clean" cases—i.e., where no other firm-specific event coincides with a split announcement—stock splits generate a positive abnormal return of close to three percent upon announcement and an additional one percent abnormal return on the ex-day. The primary contribution of this paper is to provide and empirically support a rational explanation for the split/reverse-split announcement effect.

A recent study by Ohlson and Penman [16] documents a statistical aberration, that stock volatilities increase by an average of thirty-five percent subsequent to split ex-days. In this paper, we provide a direct statistical extension of Ohlson and Penman in three directions. First, we examine reverse splits and demonstrate that they exhibit reductions in volatility. Second, we isolate the shift in volatility as between the nonsystematic and systematic components. Finally, we establish a link between trading volume and the increased volatility.

Copeland [9] shows that, contrary to "market folklore", the liquidity of a stock is actually reduced by a split. We provide a statistical extension to Copeland by examining the volume pattern of reverse splits. Copeland observes a drop in split-adjusted volume and concludes that liquidity has declined. Once again, we show that the behavior of stocks that reverse split is opposite that of splitting stocks.

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How can the positive market response be justified in light of increased risk and reduced liquidity? Is the market behaving in an irrational manner? This paper provides answers to these questions. A model is developed and tested that explains the documented market response to stock splits (including reverse splits). In particular, a stock split provides a unique opportunity to examine the "tax-option" characteristics of stock,[1] which have been presented by Constantinides [8]. It is shown that, in an efficient fashion, the market does indeed attach a value to the tax option, and this provides rationale for the otherwise inexplicable behavior observed around splits.

The remainder of the paper is organized as follows. Section I provides a brief, critical survey of extant theories of market reactions to stock splits, along with our new model of split-induced behavior. In Section II, we present our data and the standard event-study evidence. Tests of the model are presented in Section III. Section IV concludes the paper.

I. Stock Splits

A. Extant Theory

Unlike almost any other firm-specific event, stock splits and reverse splits do not involve the cash flows of the firm or any change in the relative strengths of the various interested parties of the firm (e.g., shareholders, bondholders, managers, etc.). It is with respect to the latter that the splits differ importantly from stock dividends, which involve a transfer of equity from retained earnings to the capital account. Most of the earlier literature on splits focuses on the resultant behavior of cash dividends to explain the market's response to a split (cf. [2] and [10]).

Recently, Grinblatt, Masulis, and Titman (GMT) [12] provide a thorough analysis of the market response to both stock splits and stock dividends. GMT obtain a sample of "pure" splits, i.e., a split announcement that is not contaminated by other announcements over a period of a few days. Using this sample, they observe that the market reacts favorably to a split announcement. GMT point out three standard explanations for the behavior that they observe. First, the stock split could be a means to move the stock's price into a more desirable "trading range". This presumes an affinity for (small) round-lot trading. The argument's principal weakness is that, as Branch [4] and Copeland [9] show, transactions costs (measured as a percentage of transaction value), tend to be an inverse function of stock price.

Second, the split may be a signal from management to the market that the company is undervalued. This argument requires some cost to false signalling; otherwise, it would be impossible to distinguish an undervalued splitting stock from an overvalued splitting stock. There is no such (apparent) cost in the case of stock splits. Further, it could be argued that a split provides a negative signal—that management feels that its stock price has peaked.

Finally, the split may place the stock in the limelight and serve as an attention

[1] The expression "tax option" is not meant to imply that an option-pricing model of any kind is being invoked. This merely expresses the notion that the investor has more possible tax alternatives the more volatile the stock price, ceteris paribus.

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getter. This possibility may be flatly rejected by incorporating evidence from the market response to reverse splits. As Woolridge and Chambers [20] show (and is also shown below), the market reacts unfavorably to reverse-split announcements. Thus, just getting the company's name mentioned does not always yield positive results; the market reaction to reverse splits provides evidence to reject the "attention-getting" hypothesis. GMT conclude their valuable study with the hope that "further work on these puzzling phenomena will provide additional insights" [12, p. 489].

Ohlson and Penman [16] show that, subsequent to split ex-days, stocks' volatilities increase. They explore several possible explanations for this phenomenon but ultimately conclude that it is some form of statistical aberration. In this paper, we show that this increase in volatility is a natural result of the splitting process. Further, it plays a fundamental role in the market's response to splits.

B. The Tax-Option Model

A stock split or reverse split sets off a chain of events. Upon announcement of a split, the market realizes that accompanying the resultant lower price will be an expansion in volume (measured as simply the number of shares traded daily). The increase in volume will bring about an increase in noise.[2] The nonsystematic or diversifiable risk of the stock will increase.

Most theoretical studies conclude that nonsystematic risk has no bearing on value. Empirical studies (e.g., [11]) tend to show that nonsystematic risk is unrelated to expected return. Here, we argue that the increase in diversifiable volatility results in an *increase* in the value of the firm (or a reduction in the stock's required rate of return). To understand this argument, we must first distinguish between true nonsystematic risk and the way this variable is usually measured and, second, develop an understanding of Constantinides' [8] view of a stock as embodying a tax option.

The distinction between diversifiable and nondiversifiable risk is the cornerstone of both major positive models of asset pricing: the capital asset pricing model (CAPM) and arbitrage pricing theory (APT). According to each of these theories, the diversifiable risk of a stock is not "priced" in equilibrium. The *measurement* of diversifiable risk—the variance of a security conditional upon a proper subset of the space spanned by all "systematic factors"—will typically include some systematic risk. Recent work done by Chen, Roll, and Ross [6] provides evidence that the risk of the "market portfolio" does not span the space of nondiversifiable risk. In this light, it is not surprising that early studies, e.g., by Fama and MacBeth [11], show that security risk conditional upon the market is unrelated to required return, as, in light of the tax option, this conditional variance contains both desirable and undesirable components. These studies are unable to isolate pure nondiversifiable risk.

Unlike CAPM and APT, Constantinides [8] argues that security volatility is

[2] There is now widespread evidence that trading volume and volatility of speculative price are strongly positively related. Tauchen and Pitts [19] provide a recent review of the empirical and theoretical literature in this area. The argument here is an extension of these other studies. It is supported theoretically and empirically at a later point in the text (cf. equation (2)).

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desirable, given the nature of the U.S. tax code. In particular, preferential treatment is given to long-term capital gains, and short-term capital losses may be used to offset short-term gains. A security with a price that fluctuates wildly presents its holder with the opportunity to realize losses short term or gains long term to re-establish short-term status. Constantinides argues that investors are willing to pay for a "tax-option" component of a security. Thus, securities with higher volatilities will have higher values, ceteris paribus. In terms of the CAPM or APT, the only unambiguous conclusion is that diversifiable risk becomes desirable. This implies an inverse relationship between securities' *pure* diversifiable risk and equilibrium required rates of return. Also, it means that, if a stock's diversifiable risk were subject to control by the firm's management, management would optimize shareholder wealth by pursuing policies that would increase diversifiable risk. A stock split provides a mechanism for a firm's management to raise the "tax-option" value of the stock, generating an enhancement of shareholder wealth. The nature of the stock's clientele will also change. Tax-exempt investors, for instance, will find the stock less desirable as they must forego expected return in exchange for a tax option that is worthless to them. Thus, we should observe increased trading volume around the announcement of a split. Further, since individuals tend to dominate the higher tax brackets (and institutions the lower), this tax-option effect will generally result in an increase in the number of shareholders.

II. Data and Event Study

A. *The Sample*

To reduce the problem of contamination of the split by other factors and to provide a sample of which reverse splits comprise a meaningful part, only splits of at least five for two are included. All reverse splits are included. The events are identified by searching through the CRSP tape. Thus, all such events that fall in the July 1962 through December 1985 period are included in the sample.

Table I provides a description of the data. For each event, the announcement date is verified in the *Wall Street Journal.* The event is classified as "clean" if no other mention of the company appears in the *Wall Street Journal* for the three days centered on the announcement date. The ex-date is taken from Standard and Poor's Daily Stock Price Book (ISL).

From Panel A, we see that three-for-one splits comprise sixty-eight percent of the splitting sample of 217 stocks. Also, although splits are naturally more common in bull markets, there is no apparent time-clustering problem in this sample. From Panel B, it is clear that reverse splits are rare events and are more common amongst companies listed on the American Stock Exchange than amongst those on the New York Stock Exchange. Panel C indicates that forty-seven percent of the split announcements accompany dividend announcements. Panel D provides evidence vis-à-vis the notion of the desired trading range. Of the splitting stocks, the pre-split prices span a wide range uniformly; sixty-six percent of the stocks' prices fall between twenty and sixty dollars following the split. Of the reverse-splitting sample, seventy-one percent of the stocks' prices are not more than five dollars prior to the reverse split.

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Table I

Data Description

Panel A. Forward Splits: Size, Exchange, Time

	Split Factor[a]						
	2.5	3.0	4.0	5.0	7.0	10.0	Total
By Exchange							
NYSE: Total	21	109	8	10	0	1	149
Clean	4	25	3	4	0	1	37
AMEX: Total	7	39	10	9	1	2	68
Clean	3	20	7	2	0	2	34
By Years							
1962–1965: Total	8	19	4	3	0	2	36
Clean	2	5	1	0	0	2	10
1966–1970: Total	9	46	4	4	0	0	54
Clean	4	14	1	1	0	0	20
1971–1975: Total	4	19	2	3	0	0	28
Clean	0	7	2	2	0	0	11
1976–1980: Total	4	29	3	3	1	0	40
Clean	0	9	3	0	0	0	12
1980–1985: Total	3	35	5	6	0	1	50
Clean	1	10	3	3	0	1	18

Panel B. Reverse Splits: Size, Exchange, Time

	Split Factor[b]									
	1.2	2	2.5	3.0	3.3	4.0	5.0	10.0	20.0	Total
By Exchange										
NYSE: Total	1	2	0	4	0	3	4	1	1	16
Clean	1	0	0	3	0	2	3	1	0	10
AMEX: Total	0	5	1	4	1	4	11	7	0	33
Clean	0	3	0	2	0	3	8	5	0	21
By Years										
1962–1965: Total	0	0	0	0	0	2	7	4	1	14
Clean	0	0	0	0	0	1	6	3	0	10
1966–1970: Total	0	1	0	1	0	1	1	1	0	5
Clean	0	1	0	0	0	1	1	1	0	4
1971–1975: Total	1	2	1	4	0	3	4	2	0	17
Clean	1	0	0	3	0	3	2	1	0	10
1976–1980: Total	0	1	0	2	0	1	3	0	0	7
Clean	0	0	0	2	0	0	2	0	0	4
1980–1985: Total	0	3	0	1	1	0	0	1	0	6
Clean	0	2	0	0	0	0	0	1	0	3

Panel C. Types of Concurrent Announcements ("Contamination")

Announcement	Forward Splits	Reverse Splits
Earnings	46	7
Dividends	103	2
Mergers	9	2
Others	18	1

Panel D. Distribution of Pre- and Post-split Share Prices

Price Range	Pre-split	Post-split
All (Forward) Splits		
$P \leqq 10$	1	10
$10 < P \leqq 20$	19	50

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Table I—Continued

Panel D. Distribution of Pre- and Post-split Share Prices		
Price Range	Pre-split	Post-split
$20 < P \leqq 40$	32	119
$40 < P \leqq 60$	40	22
$60 < P \leqq 80$	43	6
$80 < P \leqq 100$	57	3
$100 < P \leqq 150$	20	3
$150 < P$	1	0
	213	213
All Reverse Splits		
$P \leqq 5$	35	10
$5 < P \leqq 10$	11	19
$10 < P \leqq 20$	1	12
$20 < P \leqq 30$	2	8
	49	49

[a] Split factor defined as number of new shares exchanged for one old share.
[b] Split factor defined as number of old shares traded for one new share.

Daily trading volume on the New York Stock Exchange (Composite) is obtained for the January 1962 to June 1985 period from ISL. Daily trading volume for an average of six quarters, centered on the announcement date for each of the stocks in the sample, is likewise obtained. A total of 90,201 observations of daily trading volume on individual stocks comprise this data base.

B. Event-Time Methodology

To ascertain the impact of the announcement of a split, along with ex-day behavior, the standard event-time methodology is employed. The market model is assumed to be a means of approximating security price movement. By making the usual Gauss-Markov assumptions, significance tests on the linear error term from period t ascertain whether there is any "abnormal" price movement in that period. We say,

$$r_{it} = \hat{\alpha}_i + \hat{\beta}_i r_{mt} + \varepsilon_{it}, \tag{1}$$

where

r_{it} is the arithmetic return on security i in period t,
$\hat{\alpha}_i$, $\hat{\beta}_i$ are time-invariant linear OLS intercept and slope estimators, respectively,
r_{mt} is the arithmetic return on the CRSP equally weighted index in period t, and
ε_{it} is the error term for security i in period t.

In this study, daily (CRSP) returns are used. To estimate the $\hat{\alpha}_i$ and $\hat{\beta}_i$, $i = 1, \cdots, N$, a period of 130 days, beginning 250 days prior to the split announcement, is used for each announcement. Portfolios of the N securities are formed in event time. In this manner, we examine whether the event (announcement or ex-day) generates "abnormal" portfolio performance. To statistically test for "abnormalities" in the portfolio-return series, the variance of the portfolio error term is

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calculated using a sixty-day period beginning 120 days prior to the event. The event time is a 121-day period centered on the event date.[3]

To isolate the market response to a split, the event-time methodology is conducted on the sample of clean-split and reverse-split announcements (Tables II and IV). Ex-split date behavior for the entire (forward) splitting sample is presented in Table III and, for the clean reverse-splitting sample, in Table V.[4]

Table II

Clean Splits Only—Announcement Day Is Day 0[a]

Trading Day	AER (%)	t-Statistic (AER)	% of Daily AER > 0	CAER (%)
−60	0.575	2.048	56.92	0.575
−40	0.655	2.254	53.85	4.227
−20	−0.436	−1.499	41.54	3.910
−10	−0.498	−1.713	41.54	4.707
−9	−0.109	−0.377	43.08	4.597
−8	−0.084	−0.290	35.38	4.513
−7	0.140	0.481	58.46	4.653
−6	−0.075	−0.259	44.62	4.577
−5	0.175	0.603	55.38	4.752
−4	0.453	1.558	58.46	5.205
−3	0.045	0.155	47.69	5.250
−2	0.002	0.006	46.15	5.252
−1	0.684	2.356	52.31	5.936
0	1.819	6.263	70.77	7.755
1	2.060	7.091	76.92	9.815
2	0.486	1.674	53.85	10.301
3	−0.477	−1.644	36.92	9.824
4	−0.390	−1.344	41.54	9.433
5	−0.136	−0.469	47.69	9.297
6	−0.333	−0.147	49.23	8.964
7	−0.121	−0.416	46.15	8.843
8	0.610	2.101	50.77	9.453
9	0.408	1.405	49.23	9.861
10	−0.551	−1.899	35.38	9.310
20	0.017	0.058	44.62	8.997
40	0.231	0.795	52.31	7.316
60	−0.325	−1.120	38.46	5.150

[a] $N = 65$
Average Alpha = 0.00169
Average Beta = 1.03344
Evidence of Ex Post Selection Bias:
CAER ($t - 60$ through $t - 1$): 5.936 t-Statistic: 1.876

[3] It may be that splitting stocks do "abnormally well" during the test period and that reverse-splitting stocks do "abnormally poorly". This *could be* part of the motivation for the (reverse) split. There is no facile way to avoid this problem of ex post selection bias, and the methodology employed herein is standard in finance.

[4] For the ex-day calculations, the "pre"-time period for estimation of the return-generating process is based on the announcement day. The exception is Table VI, where the return-generating process is measured in the post-ex-day period.

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Table III

All Stock Splits—Ex-Day Is Day 0[a]

Trading Day	AER (%)	t-Statistic (AER)	% of Daily AER > 0	CAER (%)
−60	0.245	1.704	49.50	0.245
−40	0.122	0.849	47.50	0.935
−20	0.079	0.552	45.00	2.200
−10	−0.182	−1.265	44.50	1.561
−9	−0.068	−0.470	44.00	1.493
−8	0.117	0.813	45.00	1.610
−7	−0.073	−0.505	47.50	1.538
−6	−0.334	−2.324	43.00	1.203
−5	−0.166	−1.155	42.00	1.037
−4	−0.061	−0.427	45.50	0.976
−3	−0.087	−0.603	43.00	0.889
−2	−0.030	−0.212	46.00	0.859
−1	0.161	1.120	49.00	1.020
0	0.558	3.877	53.00	1.577
1	0.034	0.239	48.50	1.612
2	−0.025	−0.176	50.00	1.586
3	−0.053	−0.367	48.00	1.534
4	−0.169	−1.173	37.50	1.365
5	−0.125	−0.871	48.00	1.240
6	0.401	2.786	52.50	1.640
7	−0.119	−0.824	45.00	1.522
8	−0.212	−1.473	43.50	1.310
9	−0.199	−1.386	38.00	1.111
10	−0.183	−1.274	48.00	0.927
20	−0.257	−1.788	41.50	−1.098
40	−0.223	−1.549	40.00	−4.393
60	−0.370	−2.576	39.00	−5.858

[a] $N = 200$
Average Alpha = 0.00137
Average Beta = 1.06734
Evidence of Price Pressure:
CAER (t + 1 through t + 20): −2.710 t-Statistic: −4.240
CAER (t + 1 through t + 60): −6.749 t-Statistic: −7.470

Table IV

Clean Reverse Splits—Announcement Day Is Day 0[a]

Trading Day	AER (%)	t-Statistic (AER)	% of Daily AER > 0	CAER (%)
−60	−0.736	−0.723	34.48	−0.736
−40	−0.121	−0.119	48.28	5.521
−20	2.623	2.577	58.62	7.732
−10	0.294	0.289	44.83	4.560
−9	0.338	0.332	27.59	4.897
−8	1.754	1.723	44.83	6.651
−7	−0.911	−0.895	31.03	5.740
−6	0.188	0.185	37.93	5.928

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Table IV—Continued

Trading Day	AER (%)	t-Statistic (AER)	% of Daily AER > 0	CAER (%)
−5	0.016	0.016	51.72	5.945
−4	−1.229	−1.208	44.83	4.716
−3	2.812	2.763	51.72	7.528
−2	−0.444	−0.437	37.73	7.084
−1	−0.174	−0.171	48.28	6.910
0	−2.936	−2.885	20.69	3.974
1	−2.558	−2.514	27.59	1.415
2	0.180	0.177	48.28	1.595
3	−0.168	−0.165	37.93	1.428
4	−1.210	−1.189	34.48	0.217
5	0.808	0.794	51.72	1.026
6	0.965	0.748	48.28	1.991
7	−2.361	−2.320	27.59	−0.370
8	0.623	0.612	55.17	0.253
9	−1.857	−1.824	34.48	−1.604
10	−0.461	−0.453	44.83	−2.065
20	−0.524	−0.515	44.83	−3.590
40	−0.427	−0.420	44.83	−6.557
60	0.540	0.531	51.72	−13.558

[a] $N = 29$
Average Alpha = 0.00048
Average Beta = 1.0144
Evidence of Ex Post Selection Bias:
CAER (t − 60 through t − 1): 6.910 t-Statistic: 0.620

Table V

Clean Reverse Splits—Ex-Day Is Day 0[a]

Trading Day	AER (%)	t-Statistic (AER)	% of Daily AER > 0	CAER (%)
−60	−1.051	−1.065	37.04	−1.051
−40	−0.723	−0.733	44.44	−4.480
−20	−1.824	−1.849	29.63	−8.108
−10	0.949	0.962	51.85	−5.490
−9	−0.841	−0.852	44.44	−6.331
−8	0.328	0.332	48.15	−6.003
−7	−1.356	−1.374	29.63	−7.359
−6	0.174	0.176	44.44	−7.185
−5	−0.376	−0.381	44.44	−7.561
−4	−0.715	−0.724	37.24	−8.276
−3	−1.552	−1.572	37.04	−9.827
−2	0.023	0.024	51.85	−9.804
−1	0.033	0.034	40.74	−9.771
0	−2.157	−2.186	29.63	−11.928
1	−2.631	−2.666	18.52	−14.558
2	−1.881	−1.906	25.93	−16.440
3	−0.832	−0.843	48.15	−17.271
4	−0.836	−0.848	44.44	−18.108
5	−2.083	−2.111	44.44	−20.191
6	−0.365	−0.369	40.74	−20.555

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Table V—Continued

Trading Day	AER (%)	t-Statistic (AER)	% of Daily AER > 0	CAER (%)
7	1.079	1.093	59.26	−19.477
8	0.148	0.150	55.56	−19.329
9	0.772	0.782	44.44	−18.557
10	1.197	1.213	44.44	−17.360
20	−0.601	−0.609	29.63	−17.365
40	−0.984	−0.997	40.74	−20.803
60	−0.316	−0.320	40.74	−20.581

[a] $N = 27$
Average Alpha = 0.0002653
Average Beta = 1.0435553

Table VI

All Forward Splits—Ex-Day Is Day 0; Post-event Period Used to Measure Market Model[a]

Trading Day	AER (%)	t-Statistic (AER)	% of Daily AER > 0	CAER (%)
−60	0.342	1.988	52.45	0.342
−40	0.231	1.341	51.47	3.440
−20	0.157	0.912	48.04	6.636
−10	−0.024	−0.140	49.51	7.525
−9	0.038	0.218	49.02	7.562
−8	0.266	1.547	49.51	7.828
−7	0.121	0.702	49.51	7.949
−6	−0.085	−0.496	48.04	7.864
−5	−0.035	−0.203	45.59	7.829
−4	0.061	0.355	47.06	7.890
−3	0.087	0.498	47.55	7.976
−2	0.066	0.386	50.98	8.042
−1	0.247	1.435	50.00	8.289
0	0.668	3.883	56.37	8.957
1	0.160	0.929	49.02	9.117
2	0.061	0.355	51.96	9.178
3	0.043	0.252	48.53	9.222
4	−0.066	−0.384	42.16	9.156
5	−0.078	−0.455	48.53	9.077
6	0.398	2.310	53.43	9.475
7	−0.061	−0.356	44.61	9.413
8	−0.090	−0.521	47.55	9.324
9	−0.078	−0.455	40.20	9.245
10	0.033	0.194	50.98	9.279
20	−0.113	−0.658	46.57	8.862
40	−0.070	−0.407	41.67	8.553
60	−0.154	−0.896	46.57	9.728

[a] $N = 204$
Average Alpha = −0.0000743
Average Beta = 1.3403
Cumulative Residuals:
CAER (t + 1 through t + 20): −0.255 t-Statistic: −0.356
CAER (t + 1 through t + 60): 0.611 t-Statistic: 0.814

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In Table VI, the event study of all split ex-dates is performed using the post-split period to estimate the market model. The 130 days ending 250 days following the ex-date are used to estimate (1). The portfolio error variance is calculated using the 61st through 120th days after the ex-date. The conclusions drawn from these tables are that there is a positive abnormal market reaction to (forward) split announcements and on ex-split days. The opposite behavior is exhibited by reverse-splitting stocks on both days. These results confirm the earlier findings of GMT [12] and Woolridge and Chambers [20].

C. Daily Trading Volume

In addition to examining return series to draw inferences concerning market behavior, we also look at daily trading volume around the event. In Tables VII through X, summary volume statistics in event time are presented. In these four

Table VII

Forward Splits—Comparative Volume Statistics; Event: Announcement[a]

Date (Event Time)	$\overline{Vol}_{it}$	$\overline{Vol}_{mt}$	Mean of Ratios	Ratio of Means
−60	159.589	34.198	6.256	4.667
−40	311.411	34.283	10.569	9.084
−20	199.424	35.193	7.012	5.667
−10	272.974	36.196	9.289	7.542
−9	256.970	37.499	8.165	6.853
−8	271.270	35.621	8.935	7.616
−7	273.565	35.401	8.985	7.728
−6	336.966	36.384	10.307	9.261
−5	250.312	36.068	9.314	6.940
−4	285.253	36.385	9.217	7.840
−3	304.164	35.953	8.861	8.460
−2	256.693	36.238	8.088	7.083
−1	236.993	36.642	7.651	6.468
0	302.953	36.001	12.207	8.415
1	379.552	35.407	13.975	10.720
2	397.694	35.919	11.936	11.072
3	383.037	35.188	10.959	10.885
4	316.732	35.265	9.446	8.982
5	272.413	35.386	8.767	7.698
6	339.849	36.008	9.845	9.438
7	261.168	35.608	8.523	7.335
8	273.828	35.859	9.232	7.636
9	330.406	35.966	9.575	9.187
10	295.722	35.498	8.485	8.331
20	279.212	35.290	8.299	7.912
40	283.892	35.168	8.383	8.072
60	196.866	35.008	7.504	5.623

[a] $N = 215$
Total Observation: 73,753
Grand Mean Ratio: 6.828 Grand Std. Dev. = 19.574
(Volume post ex-day adjusted for split factor.)

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Table VIII

Forward Splits—Comparative Volume Statistics; Event: Ex-Date[a]

Date (Event Time)	$\overline{Vol_{it}}$[b]	$\overline{RVOL_{it}}$[c]	$\overline{Vol_{mt}}$	Mean of Ratios (ADJ)	Mean of Ratios (RAW)	Ratio of Means (ADJ)	Ratio of Means (RAW)
−60	319.705	319.705	34.833	11.286	11.286	9.178	9.178
−40	237.635	237.635	34.349	8.449	8.449	6.918	6.918
−20	226.835	226.835	34.448	8.160	8.160	6.585	6.585
−10	286.695	286.695	33.512	9.032	9.032	8.555	8.555
−9	286.032	286.032	34.505	8.236	8.236	8.290	8.290
−8	224.974	224.974	35.231	7.317	7.317	6.386	6.386
−7	261.376	261.376	34.566	7.865	7.865	7.561	7.561
−6	230.443	230.443	34.294	8.110	8.110	6.720	6.720
−5	254.100	254.100	33.678	8.767	8.767	7.545	7.545
−4	242.354	243.354	35.130	7.084	7.084	6.899	6.899
−3	187.643	187.643	35.208	6.538	6.538	5.329	5.329
−2	255.414	255.414	34.430	7.840	7.840	7.418	7.418
−1	259.713	259.713	33.751	8.451	8.451	7.695	7.695
0	199.882	671.081	34.323	6.920	23.320	5.824	19.552
1	230.014	798.904	34.967	6.840	23.435	6.578	22.846
2	276.588	960.794	34.819	7.678	26.076	7.944	27.594
3	293.781	1053.043	35.113	8.408	29.490	8.367	29.990
4	231.436	813.223	33.122	8.366	28.860	6.987	24.552
5	229.892	832.629	34.289	8.593	30.880	6.704	24.283
6	186.365	643.951	35.836	7.562	26.175	5.200	17.969
7	201.014	691.582	35.419	7.028	23.768	5.675	19.526
8	182.176	625.156	35.293	6.939	23.369	5.162	17.713
9	180.720	622.055	34.883	6.602	22.121	5.181	17.833
10	229.062	798.771	34.515	6.637	23.621	6.969	23.143
20	210.519	717.065	34.334	6.970	23.844	6.132	20.885
40	182.234	627.824	35.859	5.837	19.766	5.082	17.508
60	171.796	594.460	37.221	5.749	19.464	4.616	15.971
80	192.627	686.965	37.813	5.573	18.918	5.094	18.167
100	233.779	851.057	36.552	7.251	25.391	6.396	23.283

[a] Adjusted Volume: $N = 215$
Total Observation: 73,753
Grand Mean Ratio: 6.828 Std. Dev. = 19.574
t-Test for Shift on Ex-Day: $t = -8.978$
Critical t-Value at Five Percent Level of Significance: −1.645

Raw Volume: $N = 215$
Total Observation: 73,753
Grand Mean Ratio: 12.852 Std. Dev. = 46.714
t-Test for Shift on Ex-Day: $t = 36.44$
Critical t-Value at Five Percent Level of Significance: 1.645

[b] $\overline{Vol_{it}}$ is the average daily trading volume adjusted for the split (in hundreds of shares) for the sample, in event time.

[c] $\overline{RVOL_{it}}$ is the non-split-adjusted volume.

tables, the second column, entitled $\overline{Vol_{it}}$, represents the average volume of the (reverse) splitting portfolio of N securities in event time (in hundreds of shares). $\overline{Vol_{mt}}$ represents the average market volume on the N days in event time (each security counting as one day), in millions of shares traded. The ratio of column two to column three, along with the mean of the N volume ratios on day t, is also

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Table IX

Reverse Splits—Comparative Volume Statistics; Event: Announcement Day[a]

Date (Event Time)	$\overline{Vol}_{it}$	$\overline{Vol}_{mt}$	Mean of Ratios	Ratio of Means
−60	77.245	20.287	5.008	3.808
−40	103.429	22.157	7.486	4.668
−20	125.061	21.824	8.357	5.730
−10	123.061	22.154	8.042	5.555
−9	105.390	21.314	7.504	4.945
−8	107.470	21.510	8.054	4.996
−7	92.411	21.527	6.526	4.293
−6	116.777	23.242	7.267	5.024
−5	103.143	22.493	7.085	4.586
−4	87.674	21.839	5.914	4.015
−3	107.862	21.414	6.569	5.037
−2	122.696	21.799	8.083	5.629
−1	104.940	20.572	7.592	5.101
0	210.042	21.344	14.563	9.841
1	365.412	20.878	26.486	17.502
2	222.476	21.826	15.250	10.193
3	159.947	24.783	10.229	6.454
4	138.051	26.004	10.772	5.309
5	155.798	23.113	9.869	6.741
6	141.242	23.970	10.211	5.892
7	108.581	24.664	8.504	4.402
8	126.255	25.748	8.797	4.904
9	136.676	24.492	9.429	5.580
10	138.934	25.944	8.407	5.355
20	134.654	23.212	8.387	5.801
40	131.252	24.282	6.765	5.405
60	133.713	24.876	9.105	5.375

[a] $N = 49$
Total Observation: 16,448
Grand Mean Ratio: 9,306 Grand Std. Dev. = 20.889

Table X

Reverse Splits—Comparative Volume Statistics; Event: Ex-Date; Volume Adjusted for Split Factor[a]

Date (Event Time)	$\overline{Vol}_{it}$[b]	$\overline{RVOL}_{it}$	$\overline{Vol}_{mt}$	Mean of Ratios (ADJ)	Mean of Ratios (RAW)	Ratio of Means (ADJ)	Ratio of Means (RAW)
−60	117.918	117.918	20.440	6.270	6.270	5.768	5.768
−40	108.898	108.898	20.596	7.482	7.482	5.287	5.287
−20	103.265	103.265	18.335	9.279	9.279	5.632	5.632
−10	160.490	160.490	19.098	10.641	10.641	8.404	8.404
−9	112.592	112.592	19.372	7.139	7.139	5.812	5.812
−8	96.612	96.612	21.961	7.626	7.626	4.399	4.399
−7	112.122	112.122	21.885	7.137	7.137	5.123	5.123
−6	115.918	115.918	19.748	6.841	6.841	5.870	5.870
−5	106.633	106.633	19.894	7.254	7.254	5.360	5.360
−4	99.469	99.469	21.166	6.098	6.098	4.699	4.699

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Table X—Continued

Date (Event Time)	$\overline{Vol}_{it}$[b]	$\overline{RVOL}_{it}$	$\overline{Vol}_{mt}$	Mean of Ratios (ADJ)	Mean of Ratios (RAW)	Ratio of Means (ADJ)	Ratio of Means (RAW)
−3	112.775	112.775	21.363	7.390	7.390	5.279	5.279
−2	117.163	117.163	21.802	8.356	8.356	5.374	5.374
−1	139.367	139.367	21.629	9.745	9.745	6.444	6.444
0	120.086	31.224	20.208	11.199	2.394	5.942	1.545
1	157.870	35.612	20.708	12.548	2.554	7.624	1.720
2	182.108	42.408	20.369	17.325	3.336	8.940	2.082
3	183.942	48.367	20.154	12.905	2.751	9.127	2.400
4	221.852	53.408	19.754	15.388	3.102	11.231	2.704
5	252.818	67.204	21.435	12.998	3.066	11.795	3.135
6	164.566	36.265	19.684	11.798	2.387	8.360	1.842
7	233.152	52.878	19.586	13.059	2.723	11.904	2.700
8	144.699	37.163	20.004	10.816	2.191	7.234	1.858
9	156.492	38.918	20.513	9.929	2.045	7.629	1.897
10	179.423	37.551	20.970	11.687	2.068	8.556	1.791
20	115.194	29.347	20.001	7.580	1.805	5.759	1.467
40	143.595	32.939	20.009	9.408	2.004	7.176	1.646
60	397.083	65.673	22.008	13.143	2.536	18.042	2.984
80	111.967	28.122	22.902	6.035	1.624	5.357	1.345
100	151.809	49.122	23.214	9.648	2.767	6.539	2.116

[a] Adjusted Volume: $N = 49$
Total Observation: 16,448
Grand Mean Ratio: 8.862 Grand Std. Dev. = 19.914
Aggregate t-Test for Shift in Split-Adjusted Volume: $t = 3.92$
Critical Value at Five Percent Level of Significance: 1.645

Raw Volume: $N = 49$
Total Observation: 16,448
Grand Mean Ratio: 5.738 Grand Std. Dev. = 16.896
Aggregate t-Test for Shift in Raw Volume: $t = -22.70$
Critical Value at Five Percent Level of Significance: 1.645

[b] See notes to Table VIII.

presented. Dividing security volume by the market volume is done to compensate for the enormous growth in trading volume over the twenty-four-year test period. Tables VIII and X also provide data on "raw" volume. All previous studies of splits that address trading volume do so using split-adjusted volume. For reasons that will be clarified below, nonsplit-adjusted volume is important in this study.

As shown in Tables VIII and X, a t-test is conducted to test the hypothesis concerning daily trading volume in split-adjusted (or value) terms. Following Copeland's [9] hypothesis, we test whether mean market-adjusted, split-adjusted volume declines following the ex-day of a forward split. The t-statistic of −8.97 is compared with the critical t of −1.645 at the five percent significance level of a one-tailed test. On an individual security basis, of 215 splits, eighty-seven show a statistically significant (using the five percent level of significance) drop in split-adjusted, market-adjusted average daily volume, while twenty-seven exhibit a significant increase. These tests corroborate Copeland's earlier (and less powerful) study: the value of shares traded falls subsequent to the ex-split day.

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Turning to reverse splits, we may naturally presume that split-adjusted, market-adjusted volume increases following the ex-reverse-split day. Once again, the t-statistic of 3.92 (Table X) supports this conjecture. On an individual security basis, of forty-nine reverse splits, fifteen exhibit a statistically significant increase and two exhibit a significant decrease in split-adjusted, market-adjusted volume.

III. Tests of Tax-Option Model

A. Clienteles

In an early study of stock splits, Barker [2] shows that the ownership bases of firms that split increase by an average of thirty percent, while a control group of nonsplitting firms exhibits an average increase in number of shareholders for the years 1950 through 1953 of six percent.

Compustat provides data on the number of shareholders on an annual (fiscal year) basis beginning in 1975. These data were collected for all the events in our sample in the post-1975 period. Our results for forward splits are amazingly similar to Barker's. There are forty-one splitting firms with available data. These are matched with all firms in the same industry with ownership data in both years. The average number of shareholders *increases* by 34.65 percent in the year of the split for the splitting firms. The control sample of nonsplitting firms in these years exhibits an average *decline* in number of shareholders of 2.11 percent. For the five reverse-splitting firms with available data, the average number of shareholders declines by 1.92 percent. This is somewhat surprising in light of market folklore that suggests that reverse splits are sometimes undergone as a tool to reduce the number of (especially odd-lot) shareholders.

This increase in the number of shareholders is predicted by our theory. Tax-exempt institutions will not be willing to trade off lower expected returns for the tax option. From Tables VI and VII, we may infer that the increase in the number of shareholders does not imply an increase in the value of shares traded. Rather, the large abnormal market-adjusted volume that is observed on the announcement day, and especially over the next three days, is indicative of a one-time clientele shift.

B. Time Behavior of Market-Model Parameters

The first element in the tax-option model is the behavior of security volatilities pursuant to (reverse) splits. Ohlson and Penman [16] establish that, indeed, security volatility is increased subsequent to a split. Extending Ohlson and Penman, we now distinguish between systematic risk ($\hat{\beta}$) and nonsystematic risk ($\sigma^2(\varepsilon)$) (using the notation from equation (1)). The measure of volatility typically includes a bias due to discreteness in trading prices, nontrading, and the bid-ask spread. This bias will, ceteris paribus, be higher, the lower the security's price.

We examine the behavior of $\hat{\beta}$ around a (reverse) split by measuring the market-model parameters using a 150-day period ending twenty trading days prior to the *announcement* date for each event. Next, the market model is

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estimated using the 150-day period beginning twenty trading days after the *ex-date*. The Chow test is employed to test equality of $\hat{\beta}$ pre- and post-split. For two of forty-one reverse splits tested, there is evidence of significant upward shift in $\hat{\beta}$; no reverse split results in a significant decline in $\hat{\beta}$. Thirty-nine of the 201 splits show a statistically significant increase in $\hat{\beta}$ following the split. Eight of the 201 exhibit a significant drop in $\hat{\beta}$ following the split. The critical F level for our individual Chow test is 3.02. The mean F value of the forty-one reverse splits is 0.32; the mean absolute value F is 0.90. For the 201 splits, the sample mean F is 0.98, and the mean absolute value F is 1.90.

The mean $\hat{\beta}$ of the splitting sample is 1.101 in the pre-split period and 1.387 in the post-split period. The sample t-statistic of 4.114 indicates an upward shift in $\hat{\beta}$ resulting from the split. The sample t-statistic when the "clean"-splitting sample of sixty-eight stocks is used is 2.434. On the other hand, the sample t-statistic for the reverse-splitting sample is 0.828, indicating no shift in $\hat{\beta}$ around reverse splits.

To ascertain whether the documented shifts in $\hat{\beta}$ result from problems associated with nonsynchronous trading, Scholes-Williams [18] betas (SW $\hat{\beta}$) are used. The mean SW $\hat{\beta}$ of the splitting sample is 1.131 pre-split and 1.265 post-split. The sample t-statistic of 2.138 confirms the conclusion achieved with the OLS estimates. The SW $\hat{\beta}$'s for the reverse-splitting sample are 1.016 and 1.069 in the pre- and post-reverse-split periods, respectively. The sample t-statistic is 0.288, also confirming the OLS-based tests. The similarity between the SW $\hat{\beta}$'s and the OLS $\hat{\beta}$'s is an indication that problems arising from nonsynchronous trading are virtually nil for the sample of stocks that comprise this study, either pre- or post- (reverse) split.

Since the familiar Bartlett's test for a shift in variance is not robust with respect to non-Gaussian variables and it is well known that daily arithmetic stock returns are leptokurtic, Levene's $W10$ statistic is used to test for a shift in the error variance. In a simulation analysis, Brown and Forsythe [5] show that this test performs better than the alternatives in the presence of leptokurtic data. (Because of the importance of this test in our analysis, a brief description of the $W10$ statistic is provided in the Appendix.)

Levene's $W10$ tests are conducted using the same regressions as in the Chow tests above. Of the forty-one reverse splits examined, fifteen exhibit an increase in error variance that is statistically significant at the five percent level. The remaining twenty-six have a significant decrease in error variance. The critical value of the $W10$ statistic is 3.86. The sample mean $W10$ is -14.41; the mean absolute value $W10$ is 15.90.[5]

Of 201 forward splits, 192 show a significant increase in error variance; nine show a significant decrease. The sample mean $W10$ is 10.76; the mean $|W10|$ is 12.07. As our theory implies, we have strong evidence of an increase in the volatility of a security—conditional upon the market—subsequent to splits and generally opposite behavior subsequent to reverse splits.

[5] Naturally, the one-eighth effect will also affect our ability to *measure* nonsystematic risk. However, the discreteness constraint itself may indeed introduce additional *noise* to the stochastic behavior of the stock price.

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C. What Shifts Variance?

There are several factors that could explain the increased volatility following a split. First, the percentage bid-ask spread is known to be inversely related to price (cf. [3]). If closing quotes randomly occur at bid and ask prices, then the lower price—brought about by the split—will induce higher volatility. Second, the lower price may lead to increased participation of "noise traders" in the stock (cf. [7] and [19]).

Finally, despite the drop in dollar value of shares traded (or split-adjusted shares), it may be that the number of transactions per day rises following the split. Since the number of shareholders increases significantly following a split, the split has a negative impact on the size of the average transaction. Despite the small drop in split-adjusted volume, it is reasonable to expect that the number of transactions has indeed increased. Clark [7] has developed a model in which a stock's volatility is an increasing function of the number of transactions, as the Gaussian price process is subordinated to the process generating the number of transactions. Data on the number of transactions per day are not available for this sample, so raw volume is used as a proxy. Split-adjusted volume would be an inappropriate proxy in light of the large change in the number of shareholders.

For the forward-splitting sample, all but two securities exhibit a statistically significant increase in market-adjusted (raw) volume subsequent to the split. In Table VIII, raw volume, $\overline{RVOL}_{it}$, and market-adjusted raw volume (columns of ratios designated "RAW") for the sample of splitting firms are presented along with the split-adjusted volume (columns of ratios designated "ADJ"). The increase in market-adjusted raw volume appears to be permanent; no reduction is seen through one hundred trading days following the ex-day. The sample t-statistic for market-adjusted volume increase is 36.44. Of the forty-nine reverse splits, thirty-five exhibit a significant drop in market-adjusted raw volume following the split ex-date. The sample t-statistic is -5.64. Thus, *raw* volume, proxying for the number of transactions, indeed behaves as our theory would indicate.

The following three regressions show the impact of the change in raw volume, following a (reverse) split on the stock's total volatility (in (2)), systematic risk (in (3)), and diversifiable risk (in (4)), in the context of (1), for the sample of 240 splits and reverse splits; t-statistics are reported in parentheses beneath the coefficients.

$$\begin{aligned} \Delta TR &= \underset{(4.38)}{2.042} + \underset{(6.22)}{1.3232}\,t_{\Delta rmav} \\ F &= 38.70 \qquad r^2 = 13.94\% \end{aligned} \tag{2}$$

$$\begin{aligned} SCHO &= \underset{(12.40)}{3.9063} + \underset{(4.01)}{0.498}\,t_{\Delta rmav} \\ F &= 16.04 \qquad r^2 = 6.29\% \end{aligned} \tag{3}$$

$$\begin{aligned} SW10 &= \underset{(-1.034)}{-1.880} + \underset{(9.082)}{1.929}\,t_{\Delta rmav} \\ F &= 82.47 \qquad r^2 = 25.7\%, \end{aligned} \tag{4}$$

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where

ΔTR = ratio of total (daily) variance prior to the split to the total variance post-split ("pre"-period defined as 150 trading days ending twenty days before the announcement date; "post"-period defined as 150 trading days beginning twenty days following the ex-date).

$t_{\Delta rmav}$ = signed t-statistic that tests the stock's change in market-adjusted raw volume (which allows for different sample variances in the "pre"- and "post"-periods).

$SCHO$ = signed (Chow) F-statistic to test the shift in $\hat{\beta}$ around the split.

$SW10$ = signed $W10$ statistic to test the shift in error variance around the split.

These results—taken in light of Clark's model—are evidence that the (reverse) split induces an increase (decrease) in the number of daily transactions (which are smaller (larger) in terms of number of shares, on average).

D. The Tax Option

The next step is to show that the change in purely diversifiable risk changes the market value of the security through the change in the tax-option value. To test this, the sum of the abnormal return on the announcement day, the announcement day plus one, and the announcement day plus two (CAR_3^A) for each event is regressed on the signed $W10$ that pertains to that event.[6] The first regression uses all splits and reverse splits, but an event is excluded if the absolute value of the security's cumulative abnormal return from the announcement day −60 through announcement day −1 exceeds twenty-five percent. This criterion would exclude a security if its return series—relative to that in the testing period—indicates that the abnormal return on day 0 is likely to be poorly measured.[7] This yields a sample size of 179 and the following regression:

$$\begin{aligned} CAR_3^A &= \underset{(3.303)}{1.667} + \underset{(4.652)}{0.109}\ SW10 \\ F &= 21.636 \qquad r^2 = 10.89\%. \end{aligned} \tag{5}$$

[6] The results are virtually identical whether the CAER of day 0 and +1 or days 0, +1, and +2 are used in these regressions.

[7] The *Wall Street Journal* search was conducted for the three days centered on the announcement. The technique of excluding firms based on significantly large CAERs in $t-60$ through $t-1$ adds to this filter in two desirable ways:

1. Events may have taken place on, say, day −4 that have an impact on the stock's price over several days, and/or
2. Unannounced events, e.g., significant rumors, that may impact price over a long period of time are culled from the sample.

An alternative regression for the entire sample of 237 stocks is

$$\begin{aligned} CAR_3^A &= \underset{(0.18)}{0.1811} + \underset{(4.00)}{1.534}\,\%\Delta_{cv} \\ F &= 16.0 \qquad r^2 = 8.8\%, \end{aligned}$$

where $\%\Delta_{cv}$ = percentage change in conditional variance from the "pre"- to the "post"-period.

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Further, recognizing that many of the events in the above sample are "contaminated," for the next test, only those events designated "clean" are employed. (All are employed.) This allows for a sample size of ninety-three events and the following regression:

$$CAR_3^A = \underset{(0.909)}{0.727} + \underset{(4.32)}{0.176}\ SW10$$
$$F = 18.70 \qquad r^2 = 17.1\%. \tag{6}$$

Finally, to further purify the above sample, those firms with cumulative abnormal returns from days −60 through −1 that exceed twenty-five percent in absolute value are excluded. This yields a fifty-four-event sample and the following relationship:

$$CAR_3^A = \underset{(-.149)}{-0.128} + \underset{(5.20)}{0.197}\ SW10$$
$$F = 27.00 \qquad r^2 = 34.3\%. \tag{7}$$

Unlike the change in diversifiable risk, the effect of the change in $\hat{\beta}$ is ambiguous in this model. An increase in $\hat{\beta}$ would have desirable tax-option consequences but would also have undesirable risk-increasing consequences. The market impact of the shift in $\hat{\beta}$ is assessed in the following regression for the 179-stock sample used in equation (5) above:

$$CAR_3^A = \underset{(4.208)}{2.274} + \underset{(1.218)}{0.2678}\ SCHO$$
$$F = 1.48 \qquad r^2 = 0.83\%. \tag{8}$$

Employing both the shift in $\hat{\beta}$ and $\sigma^2(e)$ on this sample yields

$$CAR_3^A = \underset{(3.07)}{1.6707} + \underset{(4.46)}{0.1092}\ SW10 + \underset{(0.03)}{0.0063}\ SCHO$$
$$F = 10.75 \qquad r^2 = 10.89\%. \tag{9}$$

When viewed in concert, (5) through (9) provide strong empirical support for the tax-option model. A split will typically increase both $\hat{\beta}$ and $\sigma^2(e)$; the market reacts favorably to both because of the tax-option value but reacts negatively to the increased systematic risk. Thus, the only unambiguous result—both theoretically *and empirically*—is that the market reacts positively (negatively) to the increased (decreased) diversifiable "risk" brought about by the (reverse) split.

Finally, the tax-option model implies a drop in equilibrium expected return as (high tax-bracket) investors are willing to forego return in exchange for the "tax option". This drop is confirmed by comparing Tables III and VI. When the estimators of the market model that are computed prior to the split are used to evaluate returns subsequent to the ex-day, it is clear that the model is inappropriate—it overstates the expected return; the t-statistic of the residuals from (1) for the sixty days following the ex-day is −7.470. The portfolio $\hat{\alpha}$ from (1) drops from 0.00137 percent to −0.00007 percent following the split.

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E. Liquidity and Market Microstructure

Recent work by Amihud and Mendelson (AM) [1] focuses attention on the importance of liquidity and market microstructure on asset pricing. Liquidity is essentially the degree to which a trader is able to effect a transaction at a favorable (i.e., equilibrium) price. AM indicate that significant differences in liquidity exist cross-sectionally amongst stocks trading on organized exchanges. As we have shown, a split affects several variables, each of which is related to liquidity. First, (explicit) transactions costs are increased by a split. Branch [4] shows that, per dollar, brokerage commission costs are higher for lower priced stocks. The explicit (observed) bid-ask spread, expressed as a percentage of stock price, is known to be an inverse function of stock prices [3, 4], arising, if from nothing else, from the institutionally imposed minimum one-eighth trading increment.

On the other hand, our analysis has indicated that splitting stocks have a wider ownership base following the split and also an increase in the number of daily transactions post-split. These two effects may serve to increase a stock's liquidity post-split. For instance, there may be a reduction in the effective bid-ask spread as the probability of trading within the explicit spread is increased (although, to the extent that the one-eighth constraint is binding, this could not occur).

Nevertheless, the most telling measure of the degree of liquidity is dollar value of shares traded per unit of time. Using this as a measure, Copeland [9] concludes that splits induce permanent reductions in liquidity. Our results with daily (split-adjusted) volume support this conclusion (Tables VII through X). Also, since reverse-splitting stocks behave in an opposite fashion, virtually no other conclusion is possible.[8] Thus, the increase in the number of transactions per day, along with the number of shareholders, occurs *in spite of* the reduced liquidity. Furthermore, the consequences of the enhanced tax-option value mitigate the adverse impact that the split has on liquidity.

Does the change in liquidity following a (reverse) split induce a market reaction? Using the t-statistic on the change in split-adjusted, market-adjusted volume ($t_{\Delta smav}$) as a proxy measure for the (reverse) split-induced change in liquidity, we estimate

$$\begin{aligned} CAR_3^A &= \underset{(4.62)}{2.375} - \underset{(-1.19)}{0.21} t_{\Delta smav} \\ F &= 1.42 \qquad r^2 = 0.8\%, \end{aligned} \tag{10}$$

for the 178-event sample defined in equation (5) above. Thus, the net *change* in liquidity does not affect value. In sum, whereas it is possible to explain observed

[8] That is, it is unambiguous that a reverse split enhances liquidity. The stock's price is moved to a more desirable "trading range". The discreteness-induced problems are reduced; explicit transactions costs are reduced. Measured volatility declines, and the dollar value of shares traded rises. Yet the announcement of a reverse split elicits a negative market response. This result is only explicable under the tax-option hypothesis, which also explains the market reaction to forward splits.

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behavior using a liquidity-driven theory instead of the tax-option theory, the evidence overwhelmingly favors the latter.

F. Ex-Day Behavior

The ex-split day is the day when the actual metamorphosis into the new split shares take place. In an informationally efficient market, we would not expect to observe any price effect on this day as there is no revelation of information—or tax effect—associated with this event. However, previous research (cf. [12]) has typically shown a significantly positive abnormal return on the ex-day of splitting stocks. This is also manifest in the present sample. From Table III, we see a statistically significant 0.588 percent abnormal return on the ex-day of the splitting sample.

Consistent with the direction of this paper, we now argue that the observed ex-split day behavior is evidence of price pressures or inefficiencies in the market. Evidence of price pressures arising from other phenomena, e.g., addition of a firm to the S&P 500 (cf. [13], [15], [17], and [14]) is mounting in finance. For reasons associated with the clientele-shifting impact of the split (due to the tax option), split ex-days are also examples of price pressure.

As evidence of price pressure, observe in Table III that the positive 0.6 percent gain occurring on the ex-day and the subsequent day is completely eliminated by day 10. This is weak evidence, however, as, according to our theory, the expected returns of the splitting securities (i.e., $\hat{\alpha}$) with $\hat{\beta}$ constant should fall in the post-split period as an equilibrium result. When the 120-day period ending 250 days after the ex-day is used to calculate the market-model parameters (see Table VI), the nature of the ex-day return is unaffected; the day-0 abnormal return is 0.668 percent (with a t-statistic of 3.88). However, the subsequent drop from days +1 through +20 is only 0.255 percent (with a t-statistic of -0.36). The ex-day gain is entirely eliminated from the splitting (event-time) portfolio by the forty-second day following the ex-day, even when the post-period is used for measurement, however. From Table V, we see that the reverse-splitting group exhibits a negative drop of 6.669 percent over the ex-day and the next two days of trading.

To further explore the nature of this ex-day phenomenon, two additional, cross-sectional tests are conducted. First, the price-pressure-clientele argument suggests a positive correlation between the abnormal return on the announcement and the abnormal return on the ex-day. To test this, the sum of the ex-day, ex-day plus one, and ex-day plus two abnormal returns (CAR_3^x) is regressed on the abnormal announcement-period return (CAR_3^A), for 172 (forward) splits, a split was eliminated if the absolute-value, abnormal return for the sixty days prior to the *announcement* day exceeded twenty-five percent.

$$\begin{aligned} CAR_3^x = \; & -0.990 \; + \; 0.236\, CAR_3^A \\ & (-1.715) \quad\;\; (3.542) \\ & F = 12.54 \qquad r^2 = 6.9\%. \end{aligned} \tag{11}$$

The second test involves using the percentage change in the number of shareholders ($PCNS$) as a proxy for the clientele shift. For forty-six firms with

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absolute-value, cumulative abnormal returns for the sixty days preceding the ex-day that were less than twenty-five percent, we estimate

$$\begin{aligned} CAR_3^x = \; & -1.347 + 0.132PCNS \\ & (-0.91) \quad\;\; (2.53) \\ F = 6.42 & \qquad r^2 = 12.73\%. \end{aligned} \tag{12}$$

The positive and significant coefficient on *PCNS* supports the price-pressure hypothesis as those firms with the largest increase in shareholders will, ceteris paribus, have the most trading activity—related to clientele shifting—around the ex-day. (There is no significant relationship between *PCNS* and CAR_3^A.) The accumulated weight of the evidence from this section lends support to the price-pressure hypothesis.

IV. Conclusions

The positive (negative) abnormal return to the announcement of a large split (reverse split) has been explained in the context of Constantinides' "tax-option" model. The split results in an increase in the number of transactions along with the number of shares traded, which increases the volatility of the price series. That portion of the increase in volatility that is diversifiable is *desirable*, particularly to investors in high tax brackets, as it expands the tax opportunities of owning the stock. Liquidity is generally reduced by a split and increased by a reverse split, but there is no indication that the market attaches any value to this change in liquidity. The expected rate of return of a reverse-splitting stock falls (rises) according to the theory.

As the tax-option hypothesis implies, a significant increase in the number of shareholders—and the trading volume—around the announcement of a split is observed. Once again, this occurs *in spite of*, not due to, the reduction in liquidity. By including reverse splits in this study, the hypothesis that it is the event's movement of the stock into a more favorable trading range that results in a positive market reaction was rejected.

Finally, the puzzling ex-day behavior of splits was examined. There is evidence that the abnormal ex-day behavior is some form of price pressure. The size of the ex-day abnormal return is positively related to the announcement effect, but the causes of the two effects are different. While the announcement effect reflects market valuation, the ex-day effect is related to clientele shifting.

Nowhere in this study was the motivation for stock splits investigated. Whereas the market values a split because of the tax-option consequences, this may be unrelated to management's motives for implementing the split. Management may, for instance, feel that the split will widen the ownership base, due, perhaps, to a trading-range hypothesis. A wider ownership base may appeal to management as a means of job protection as unwelcome takeovers are made more difficult. What was shown here is that whatever management's motives for declaring a split, the market attaches a positive value to the split because of its tax-option impact.

Finally, in light of the new tax bill, which will eliminate any distinction

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between long- and short-term capital gains, the market impact of splits is expected to be greatly diminished.

Appendix

The Levene W test is essentially a one-way ANOVA statistic to test for equalities of variances across g groups with known, or equal, means. In this paper, the values are OLS residuals, in a pre- and post-period; thus, we are dealing with a (g =) 2-group case, with known and equal means of zero. The test allows for different sample sizes, but, in this paper, the sample sizes are held constant (n = 150). For the case of two groups of equal size, the $W10$ statistic is

$$W10 = \frac{n(\bar{x}_1 - \bar{x})^2 + n(\bar{x}_2 - \bar{x})^2}{\left[\sum_{i=1}^{n} (x_{i_1} - \bar{x}_1)^2 + \sum_{i=1}^{n} (x_{i_2} - \bar{x}_2)^2\right] / 2n - 1}, \tag{A1}$$

where

$x_{ij} = | e_{ij} - \bar{e}_j^T |$ for $i = 1, \cdots, 150$ and $j = 1, 2$,
$\bar{x}_j = \sum_{i=1}^{n} (| e_{ij} - \bar{e}_j^T |)/n$ for $j = 1, 2$,
$\bar{x} = (\bar{x}_1 + \bar{x}_2)/2n$,
e_{ij} = the n OLS residuals from the market model, when $j = 1$ in the pre-split period and when $j = 2$ in the post-split period, and
$\bar{e}_j^T$ = ten percent trimmed mean of e_{ij} for $j = 1, 2$ and $i = 1, \cdots, n$.

The ten percent trimmed mean (or the eighty percent truncated mean) is the mean of eighty percent of these e values, from which we exclude the highest and lowest ten percentiles (when the values are placed in ascending order). The $W10$ statistic is distributed F with $g - 1$ (1) and $2n - 2$ (298) df.

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