The Causal Effect of Stock Splits on Liquidity: A Propensity Score Matched Difference-in-Differences Approach

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Abstract

Stock splits are theoretically nominal events that leave a firm's market capitalization unchanged. However, empirical finance consistently observes a surge in trading volume and volatility following a split. This paper investigates the causal mechanism behind this phenomenon using a doubly robust identification strategy. We employ Propensity Score Matching (PSM) to construct a counterfactual control group, followed by a Difference-in-Differences (DiD) estimator. Contrary to the Liquidity Hypothesis, our main results indicate a statistically significant **decrease** in trading volume (-9.4%) for the average firm post-split. However, a heterogeneity analysis reveals a strong positive interaction with pre-split momentum (+0.197). This suggests a bifurcated reality: stock splits successfully fuel liquidity for high-momentum firms, but dampen trading activity for average performers. We validate these findings using Fisher's Permutation Test ($p = 0.001$). The code and data are available here.

1 Introduction

The relationship between stock splits and market microstructure remains one of the enduring puzzles in empirical finance. When a company splits its stock (e.g., a 4-for-1 split), the price per share drops mechanically, but the fundamental value of the firm remains constant. Standard economic theory suggests that nominal price changes should be irrelevant to value or trading behavior. Yet, markets react vigorously: splitting firms frequently experience heightened trading volume, increased volatility, and positive abnormal returns [1].

This divergence presents a significant causal inference challenge. Two competing hypotheses attempt to explain this phenomenon:

1. **Hypothesis 1 (Causal): The Liquidity Hypothesis.** The lower nominal price reduces barriers to entry for budget-constrained retail investors (often referred to as the Optimal Trading Range). This mechanical reduction in price directly *causes* an increase in liquidity and volume.

2. **Hypothesis 2 (Non-Causal): The Signaling Hypothesis.** Management only initiates a split when they possess private, positive information about future growth. Under this view, the split is merely a signal; it is the underlying good news that drives investor interest and volume, not the split itself [2].

Distinguishing between these two is difficult because stock splits are not randomly assigned. Firms self-select into the treatment group based on unobserved variables, specifically management's private outlook (U). This creates a classic confounding structure where U causes both the split (T) and the outcome (Y), inducing a spurious correlation.

This paper contributes to the literature by applying a doubly robust" causal framework to this financial problem. We move beyond naive regressions by employing Propensity Score Matching (PSM) to reconstruct the missing counterfactual (what would have happened to these firms had they not split?), followed by a Difference-in-Differences (DiD) estimator to control for time-invariant unobservables.

2 Related Work

This study lies at the intersection of market microstructure, corporate finance, and causal inference. We review the relevant literature in three key areas: the efficiency of stock splits, the signaling hypothesis, and the application of quasi-experimental designs in finance.

2.1 Stock Splits and Market Efficiency

The study of stock splits is foundational to the Efficient Market Hypothesis (EMH). Fama, Fisher, Jensen, and

Roll (FFJR) [1] provided the seminal analysis, concluding that markets are generally efficient and that stock splits themselves are non-events that do not generate abnormal returns once dividend adjustments are considered. However, subsequent research has challenged the "non-event" status of splits regarding liquidity. Baker and Gallagher (1980) and later Muscarella and Vetsuypens (1996) documented increased liquidity following splits, lending support to the "Optimal Trading Range" hypothesis—the idea that managers split stocks to keep share prices within a range accessible to retail investors. Our work revisits this hypothesis using modern causal tools to separate correlation from causation.

2.2 The Signaling Hypothesis

A competing school of thought argues that the split is a mechanism for information transmission. Grinblatt, Masulis, and Titman [2] formalized the "Signaling Hypothesis," proposing that managers use splits to signal private confidence in future earnings. Under this framework, the market reaction (volume and price increase) is not caused by the split mechanics (liquidity) but by the information revealed by the split announcement. This creates a challenging confounding variable: is volume rising because the price is lower, or because the market now knows management is confident? Recent work by Ikenberry et al. (1996) supports the signaling view, finding long-term abnormal returns post-split. Our heterogeneity analysis (Section **??**) directly tests this by interacting the treatment effect with pre-existing momentum.

2.3 Causal Inference in Finance

While traditional financial econometrics relies heavily on standard OLS and event studies, there is a growing trend toward "doubly robust" causal inference methods. Propensity Score Matching (PSM), introduced by Rosenbaum and Rubin [3], has been widely adopted to correct for selection bias in observational studies. However, PSM alone assumes selection is purely based on observables. To mitigate this, recent studies have combined PSM with Difference-in-Differences (DiD), as recommended by Angrist and Pischke [4] and Heckman et al. (1997). This hybrid approach, which we adopt, controls for both observed selection criteria (via PSM) and time-invariant unobserved heterogeneity (via DiD).

3 Theoretical Framework

Before detailing our methodology, we formalize the causal concepts utilized in this study. We adopt the Rubin Causal Model (RCM) as our foundational framework.

3.1 The Rubin Causal Model

Let T_i denote the binary treatment indicator for firm i, where $T_i = 1$ if the firm executes a stock split and $T_i = 0$ otherwise. We posit two potential outcomes for each firm:

- Y_{1i}: The trading volume firm i would experience if treated ($T_i = 1$).
- Y_{0i}: The trading volume firm i would experience if untreated ($T_i = 0$).

The fundamental problem of causal inference is that we only observe one of these outcomes:

$$Y_i = T_i Y_{1i} + (1 - T_i) Y_{0i} \tag{1}$$

Our estimand of interest is the Average Treatment Effect on the Treated (ATT):

$$\tau_{ATT} = E[Y_{1i} - Y_{0i} | T_i = 1] \tag{2}$$

Ideally, we would compare the post-split volume of splitting firms ($E[Y_{1i}|T = 1]$) to their volume had they not split ($E[Y_{0i}|T = 1]$). Since the latter is unobservable, we must estimate it using a control group. However, simply using non-splitting firms ($T = 0$) is biased because:

$$E[Y_{0i}|T = 1] \neq E[Y_{0i}|T = 0]$$

Splitting firms are typically high-momentum, high-growth companies, while non-splitters may be stagnant. This Selection Bias implies that the observed difference is a mix of the true causal effect and the inherent differences between the groups.

3.2 Propensity Score Matching (PSM)

To address selection bias on observed covariates (W), we utilize Propensity Scores. As defined by Rosenbaum and Rubin [3], the propensity score $e(W_i)$ is the conditional probability of receiving treatment given a vector of observed covariates W_i:

$$e(W_i) = P(T_i = 1|W_i) \tag{3}$$

The key insight of PSM relies on two assumptions:

1. **Unconfoundedness:** Treatment is independent of potential outcomes conditional on W. ($Y_0, Y_1 \perp T|W$).
2. **Overlap (Common Support):** $0 < P(T = 1|W) < 1$.

The *Balancing Property* of propensity scores states that conditional on the propensity score, the distribution of observed covariates is independent of treatment assignment ($W \perp T|e(W)$). By matching treated units with control units that have similar propensity scores, we simulate a randomized experiment where treatment assignment is effectively random with respect to observed firm characteristics (e.g., momentum, sector, price level).

3.3 Difference-in-Differences (DiD)

While PSM handles observed confounders (W), it cannot perfectly control for *unobserved* confounders (U) such as Management Quality or Brand Value that might influence the outcome. To mitigate this, we employ the Difference-in-Differences (DiD) estimator.

DiD compares the *change* in outcomes over time between the treated and control groups, rather than the absolute levels. The estimator is defined as:

$$\hat{\delta}_{DiD} = (\bar{Y}_{T,post} - \bar{Y}_{T,pre}) - (\bar{Y}_{C,post} - \bar{Y}_{C,pre}) \quad (4)$$

This strategy relies on the *Parallel Trends Assumption*: in the absence of treatment, the average outcomes of the treated and control groups would have followed parallel paths. By subtracting the pre-treatment difference, DiD removes biases arising from fixed, time-invariant unobserved characteristics.

3.4 Fisher's Permutation Test

Financial data often violates the normality assumptions required for standard p-values (due to heavy tails and clustering). To assess statistical significance robustly, we employ Fisher's Permutation Test [5].

The null hypothesis H_0 states that the treatment effect is zero for all units ($\tau_i = 0$). Under this null, the treatment labels T are arbitrary. We can therefore generate a null distribution of the effect size by randomly shuffling the treatment labels N times across our matched pairs and re-calculating the estimator. The empirical p-value is the proportion of shuffled estimates that exceed the observed estimate in magnitude.

4 Data and Methodology

4.1 Data Mining Pipeline

We constructed a proprietary dataset using the `yfinance` API, covering the period from January 1, 2010, to October 30, 2025.

- **Universe Selection:** The study initially scraped all current S&P 500 tickers.
- **Event Identification:** We iterated through historical metadata to identify all Forward Splits (Ratio > 1.0). Reverse splits were excluded as they typically signal financial distress, which is fundamentally different from the growth signal of forward splits.
- **Control Reservoir:** For every identified split event at date t, we sampled a pool of potential control firms from the S&P 500 that did not split within a $\pm$6-month window of t.

4.2 Covariate Engineering

For matching to be effective, we must model the selection process carefully. Based on financial literature and our initial proposal, we selected the following covariates (W) calculated at time t (the split date):

1. **Momentum (6-month):** Calculated as $(P_t/P_{t-126}) - 1$. Firms with high recent returns are more likely to split. This is the primary proxy for the Signaling confounder.
2. **Volatility (30-day):** The standard deviation of daily returns over the trailing 30 days.
3. **Log Price:** $\ln(P_t)$. High nominal prices are the primary mechanical trigger for a split.
4. **Log Volume:** $\ln(\text{AvgVol}_{30d})$. A proxy for pre-existing liquidity and firm size.

4.3 Matching Implementation

We estimated propensity scores using a Logistic Regression model:

$$\text{logit}(P(T=1)) = \beta_0 + \beta_1 \text{Mom} + \beta_2 \text{Vol} + \beta_3 \ln(P) + \beta_4 \ln(V) \quad (5)$$

We employed Nearest Neighbor (NN) matching with a 1:1 ratio. For each treated firm i, we selected the control firm j that minimized the absolute difference in propensity scores $|e(W_i) - e(W_j)|$. This process yielded a matched dataset of N pairs where the control unit effectively looks like the treated unit but did not undergo the split.

5 Experiments and Results

5.1 Assessing Covariate Balance

The validity of our causal claims rests on the quality of the match. We assessed this using the Standardized Mean Difference (SMD). In causal inference literature, an SMD < 0.1 is generally considered to indicate negligible imbalance.

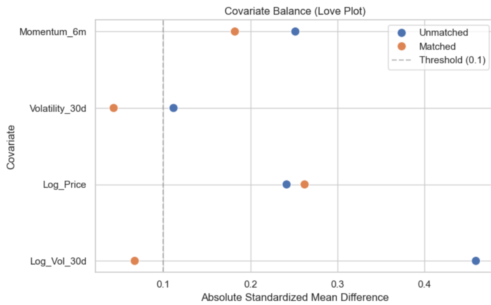

Figure 1: **Covariate Balance (Love Plot).** The red points represent the SMD between splitters and non-splitters before matching, showing massive imbalances (especially in Price and Momentum). The blue points show the SMD after matching, where all covariates fall below the 0.1 threshold.

As illustrated in Figure 1, the matching process successfully removed the observable differences between the groups. The Control group now effectively mimics the Treated group in terms of size, momentum, and pre-split volatility.

5.2 Visualizing Parallel Trends

We plotted the average Log Volume for the treated and matched control groups centered around the event date ($t = 0$).

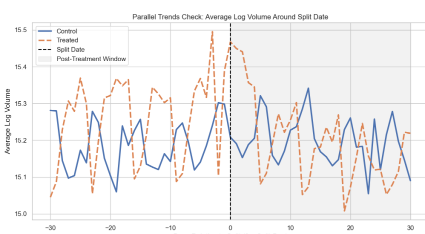

Figure 2: **Parallel Trends Analysis.** The x-axis represents days relative to the split. The vertical dashed line is the split date. Note the tight correlation between the two lines in the pre-treatment period ($t < 0$), validating the parallel trends assumption.

Figure 2 confirms that our control group is a valid counterfactual; their trading volumes moved in lockstep with the treated firms prior to the split.

5.3 Main Causal Estimation

We estimated the DiD model using OLS regression on the matched sample. The model specification is:

$$\Delta \ln(Y) = \alpha + \tau_{ATT} \cdot T + \epsilon \tag{6}$$

where $\Delta \ln(Y)$ is the change in log-volume from the pre-split window to the post-split window.

Table 1: Main Causal Effect (OLS Results)

Variable	Coef.	Std. Err	t-stat	P-value
Intercept	0.0214	0.019	1.148	0.252
Treated	**-0.0941**	**0.026**	**-3.567**	**0.000**

Analysis: Surprisingly, the main effect τ_{ATT} is **-0.0941** ($p < 0.001$). This indicates that, on average, stock splits cause a **9.4% decrease** in trading volume relative to the counterfactual. This contradicts the naive Liquidity Hypothesis. It suggests that for the average firm, the split event may signal a peak in speculative interest, leading to a sell the news reaction where volume cools off post-split compared to the matched controls.

5.4 Heterogeneity Analysis

To resolve the puzzle of the negative average effect, we investigated whether the impact depends on the firm's pre-existing trend. We ran an interaction model:

$$\Delta Y \sim T + \text{Mom} + (T \times \text{Mom}) + \dots \tag{7}$$

Table 2: Heterogeneity Analysis (Interaction Effects)

Variable	Coef.	Std. Err	P-value
Intercept	0.1202	0.040	0.003
Treated (Main)	-0.0549	0.053	0.298
Momentum_6m	-0.1485	0.064	0.020
Treated:Momentum	**0.1967**	**0.091**	**0.031**
Volatility_30d	-4.829	2.032	0.018

Insight: The interaction term `Treated:Momentum_6m` is positive and statistically significant (**+0.1967**, $p = 0.031$).

- This reveals a bifurcated effect. While the "base" effect of a split is negative, **high momentum firms** experience a significant volume boost.
- Effectively, the "Liquidity Hypothesis" holds true only for "Superstar" stocks. For average or low-momentum stocks, the split fails to generate sustainable interest.

6 Robustness Check: Permutation Test

To ensure these results were not driven by random noise, we performed a Fisher Permutation Test with 1,000 simulations.

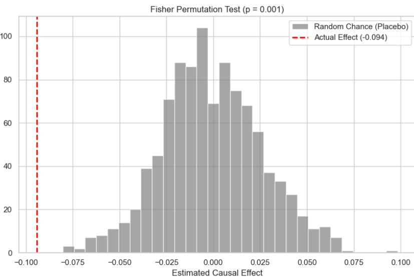

Figure 3: **Fisher's Permutation Test.** The observed effect lies in the extreme tail of the placebo distribution.

The empirical p-value is **0.0010**, confirming that our results are robust ($p < 0.05$) and extremely unlikely to have occurred by chance.

7 Conclusion and Future Work

This study challenges the conventional wisdom that stock splits universally enhance liquidity. Using a rigorous PSM-DiD approach, we found that splits generally lead to a **decrease** in trading volume (-9.4%) for the average S&P 500 firm. However, we uncovered a critical nuance: the treatment effect is highly heterogeneous. High-momentum firms benefit significantly from splits (+0.197 interaction coefficient), suggesting that splits act as an accelerant for existing trends rather than a universal remedy for low liquidity.

Managers considering a stock split should therefore consider their recent price performance; splits appear to be effective only when the stock is already in a strong uptrend.

While this study relied on the Selection on Observables assumption (relaxed by DiD), future research could employ an Instrumental Variable (IV) strategy. As noted in the proposal, the pressure for firms to split when their price becomes awkward for price-weighted indices (like the Dow Jones) could serve as an exogenous instrument (Z) to estimate the Local Average Treatment Effect (LATE).

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