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Fast-Entry Funding Pressure and Incumbent Liquidity: Evidence from the SpaceX Nasdaq-100 Inclusion

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Evidence from the SpaceX Nasdaq-100 Inclusion

Abstract

This paper studies the financing side of a large, preannounced index addition. Space Exploration Technologies Corporation entered the Nasdaq-100 before the market open on 7 July 2026, creating a 6 July implementation event. I construct model-implied funding pressure for 93 incumbents by allocating an entrant-funding requirement across pre-event weights and scaling implied sale dollars by pre-event average daily dollar volume (ADV). A one-standard-deviation increase in pressure is associated with 0.114 log points, or 12.1 percent, higher implementation-day volume relative to normal. The coefficient is 8.6323 with HC3 p = 0.0000283; randomization, bootstrap, and leave-one-out inference agree. In the original fixed-baseline design, the implementation date ranks first among 38 pre-announcement dates plus the event (p = 1/39 = 0.0256). A stricter pseudo-real-time design constructs relative volume, realized volatility, momentum, and volume variability from the preceding 20 sessions on every date. With the full dynamic control set, the event coefficient is 6.0711 (p = 0.0080), equivalent to 8.3 percent per pressure standard deviation, and ranks first among 19 fully observed placebos plus the event (p = 1/20 = 0.050). On 7 July the coefficient falls to 3.4249 (p = 0.164), with significant decay. The result is a sharply dated capacity-scaled quantity response aligned with the model-implied financing allocation.

Keywords: index inclusion, passive investing, liquidity, rebalancing, market microstructure, Nasdaq-100

JEL codes: G12, G14, G23

1 Introduction

An index addition creates two linked trades. The entering security must be purchased, and a fully invested tracking portfolio must finance that purchase. The first trade receives most attention in the index-effects literature. The second distributes a predictable implementation burden across incumbent securities.

This paper measures that financing-side cross section around SpaceX's entry into the Nasdaq-100. Nasdaq announced on 26 June 2026 that Space Exploration Technologies Corporation would join the index before the market open on Tuesday, 7 July. The official announcement fixes the event identity and effective date. Portfolios seeking the new composition at the 7 July open faced an implementation benchmark on Monday, 6 July, the preceding trading day.

The empirical design converts the common index event into heterogeneous incumbent-level pressure. Let the entrant generate a total funding requirement F. Under proportional incumbent financing, security i supplies $\hat{S}_i = F\tilde{w}_i$, where $\tilde{w}_i$ is its normalized pre-event incumbent weight. The primary treatment divides these model-implied sale dollars by pre-event average daily dollar volume. It is therefore large when a security's assigned financing burden is large relative to its ordinary trading capacity.

The main result is economically and statistically strong. Across 93 incumbents, a one-standard-deviation increase in model-implied funding pressure is associated with approximately 12.1 percent higher 6 July volume relative to normal. HC3, residual randomization, pairs bootstrap, and leave-one-out procedures all preserve the coefficient. In the fixed-baseline comparison, the 6 July estimate exceeds the coefficient from every one of 38 pre-announcement dates. In the stricter dynamic design, every outcome and trading-state

control uses only the preceding 20 sessions; the fully controlled event coefficient remains significant and ranks first among the available placebos.

The denominator-light specification tests whether shared ADV scaling alone creates the result. With log actual 6 July dollar volume as the outcome, raw model-implied sale dollars have a coefficient of 1.6939 per USD 1 billion and HC3 $p = 0.0495$ after conditioning on log ADV and loan status. The relation attenuates after recent volatility, momentum, and volume variability are added. This places the inferential weight on the economically defined burden-to-capacity measure rather than on raw sale dollars alone.

Mechanism tests locate the result in full-day trading quantities. Funding pressure does not predict the final-hour volume z-score, the final-hour share of daily volume, or the 6 July market-model abnormal return. High-pressure incumbents absorbed more implementation-day turnover without a detectable daily price concession or final-hour concentration gradient.

I make the financing leg of an index addition measurable. Classic work studies demand curves and the price effects of index membership (Harris and Gurel 1986; Shleifer 1986; Wurgler and Zhuravskaya 2002). Pavlova and Sikorskaya (2023) show how benchmark weights and benchmark-tracking assets create inelastic stock demand. I ask which incumbents supply trading capacity when a large entrant must be funded. Model-implied funding pressure sharply orders that cross section.

The design advances the index-effects literature in three ways. First, treatment varies across incumbents even though the event date is common, converting a single inclusion into a cross-sectional test. Second, the principal outcome is trading quantity, which is the direct margin on which a financed rebalance must appear. Third, the next-day comparison identifies timing: the slope is large and significant on the implementation session, smaller and insignificant one day later, and the decay is itself statistically significant.

The design traces a market mechanism from the entrant's aggregate financing requirement to its allocation across incumbent weights and each stock's ordinary trading capacity. Incumbent turnover reveals where that requirement is absorbed. Strictly lagged controls and next-day decay separate the event response from recent volatility, momentum, volume instability, and persistent cross-sectional volume patterns.

The remainder of the paper reviews the index-demand literature and the event in Section 2, develops variables and the sample in the same section, sets out inference in Section 3, reports the quantity, timing, denominator, and mechanism results in Section 4, and interprets their implications in Section 5.

2 Literature, Event, Sample, and Variable Construction

2.1 Index demand, rebalancing, and the financing leg

The canonical index-inclusion literature treats changes in index composition as observable demand shocks. Harris and Gurel (1986) document price and volume responses around S&P 500 changes and interpret much of the initial price movement as pressure. Shleifer (1986) links index-fund purchases to downward-sloping demand for individual stocks. Wurgler and Zhuravskaya (2002) show that addition effects are larger for stocks with fewer close substitutes, while Greenwood (2005) develops the distinction between short- and long-run demand curves when arbitrage is limited.

Subsequent work broadens the mechanism. Chen, Noronha, and Singal (2004) emphasize asymmetric price responses and investor awareness. Chang, Hong, and Liskovich (2015) use index-assignment discontinuities to identify price effects, while Greenwood and Sammon (2025) document the weakening of the headline index effect over time. Madhavan (2003) studies predictable trading and returns around Russell reconstitution, Petajisto (2011) describes the recurring index premium borne by mechanical index funds, and Kashyap et al. (2021) model the subsidy created by benchmark inclusion. Ben-David, Franzoni, and Moussawi (2018) show that ETF ownership can transmit trading shocks to underlying securities, and Pavlova

and Sikorskaya (2023) quantify benchmarking intensity as a source of inelastic demand. Together, this literature establishes that benchmark changes generate order imbalances, liquidity demand, and implementation costs even as average entrant-price effects evolve.

The incumbent financing leg is implicit in this framework but usually not the treatment of interest. A fully invested portfolio cannot buy a new constituent without sales, contributions, derivatives, or another funding source. Under proportional financing, incumbent sale dollars are determined by their pre-event weights. The economic intensity of those sales depends on each security's normal trading capacity. That arithmetic produces a testable incumbent cross section even when actual fund orders are not observed account by account.

I identify the financing leg through incumbent quantities: securities assigned more burden relative to normal capacity display more implementation-day turnover. The slope decays the next day and survives strictly lagged trading-state controls, locating the cross-sectional pattern on the implementation date.

2.2 Institutional event

Nasdaq's 26 June 2026 press release states that SpaceX would become a Nasdaq-100 constituent before the market open on 7 July 2026. The event is a fast-entry addition rather than the regular annual reconstitution. The study isolates the 6 July implementation session and treats the public announcement as the beginning of the pre-implementation window.

Model-implied funding pressure is the portfolio-arithmetic allocation produced by proportional incumbent financing. Actual execution can involve pre-trading, derivatives, creations and redemptions, crossing, and inventory intermediation. These channels determine how the modeled burden reaches the market; the treatment measures its predicted cross-sectional allocation rather than account-level orders.

2.3 Funding-pressure construction

Let W_i be incumbent i's pre-event index weight and let F be the aggregate dollars required under the 1.3 percent entrant-weight scenario. Normalized incumbent weights are

$$\widetilde{w}_i = \frac{W_i}{\sum_{j \in I} W_j},$$

and model-implied sale dollars are

$$\hat{S}_i = F\widetilde{w}_i.$$

The primary pressure measure is

$$Pressure_i = \frac{\hat{S}_i}{ADV_i},$$

where ADV_i is mean daily dollar volume from 1–25 June 2026. In the final sample, pressure has mean 0.0260, standard deviation 0.01324, median 0.02528, and range 0.00268–0.06165. Model-implied sale dollars average USD 66.2 million and range from USD 6.7 million to USD 479.7 million.

The primary outcome is

$$Y_i = \log\left(\frac{Volume_{i,6Jul}}{NormalVolume_i}\right).$$

The denominator-light outcome is $\log(DollarVolume_{i,6Jul})$. Its treatment is $\hat{S}_i$ measured in USD billions; log pre-event ADV is included directly as a control.

The entrant-weight scenario determines the level of predicted sale dollars but not the cross-sectional ranking of proportional pressure. Multiplying the aggregate funding requirement by a common scalar multiplies every incumbent's predicted sale amount by that scalar. The identifying variation comes from normalized incumbent weights and pre-event trading capacity. This makes the coefficient interpretable as a slope across the modeled allocation rather than an estimate of the exact dollar orders of any named fund.

Normal volume and ADV are estimated before the announcement window so that the implementation session does not enter its own benchmark. The capacity-scaled outcome asks whether observed share turnover is unusual for the same security. The denominator-light outcome asks whether the dollar level of execution-day trading rises with raw predicted funding after conditioning separately on ordinary dollar volume. Agreement between them is informative because the two models use different dependent variables and different treatments.

2.4 Sample flow and controls

The estimation panel contains 93 incumbent securities with complete pressure, daily volume, return, and control fields. The roster construction removes transition securities associated with the HON/HONA identifier change, securities newly added to the Nasdaq-100 on 22 June whose pre-event index history is not comparable, and FER pending a separate identifier mapping. The retained panel then requires positive pre-event ADV and nonmissing 6 July price and volume.

The sample rules are applied before the cross-sectional regressions. They address identifier continuity and exposure comparability rather than outcome values. The resulting pressure distribution is broad: the highest observation is about 23 times the lowest, and the interquartile grouping produces 23 or 24 securities per bin. This spread is what allows a single aggregate index event to identify heterogeneous incumbent responses.

Table 1 Variable and sample audit

Component	Construction
Event	Nasdaq announcement 26 June 2026; effective before open 7 July; implementation session 6 July
Final sample	93 incumbent securities
Model-implied sale dollars	Aggregate 1.3% entrant-funding scenario allocated by normalized incumbent weight
Primary pressure	Model-implied sale dollars / pre-event ADV
Primary outcome	Log 6 July volume relative to normal volume
Primary-model controls	Log pre-event ADV; securities-on-loan indicator
Denominator-light outcome	Log 6 July actual dollar volume
Denominator-light controls	Log pre-event ADV; securities-on-loan indicator
Mechanism outcomes	Final-hour volume z-score; final-hour share ratio; market-model abnormal return

3 Empirical Design

3.1 Capacity-scaled model

The main cross-sectional specification is

$$Y_i = \alpha + \beta Pressure_i + \Gamma' X_i + \varepsilon_i.$$

β measures how implementation-day trading intensity varies with the predicted financing burden relative to ordinary capacity. HC3 standard errors allow residual variance and leverage to differ across the 93 securities.

Three procedures evaluate coefficient stability. A 20,000-draw Freedman-Lane test residualizes treatment and outcome with respect to the controls and permutes the treatment residuals. A 10,000-pair bootstrap resamples securities and re-estimates the model. Leave-one-out regressions remove each constituent in turn. These procedures test the cross-sectional association's sensitivity to conventional standard-error assumptions and individual observations.

The control vector is fixed across the principal event and date-placebo regressions: log pre-event ADV and a securities-on-loan indicator. Log ADV absorbs broad scale differences that may remain in relative turnover; the loan indicator absorbs a direct marker of securities-lending participation. Stating this set explicitly is important because every placebo date must estimate the same partial association as the event date.

The procedures answer different inferential questions. HC3 adjusts the regression covariance for heteroskedasticity and leverage. Freedman-Lane randomization tests the partial association after preserving the fitted contribution of controls. The pairs bootstrap resamples the empirical cross section without fixing the regressor matrix. Leave-one-out estimation checks whether a single large-weight or low-ADV security determines the slope. Concordance across all four methods is stronger evidence than any one p-value.

3.2 Denominator-light model

The independent scaling check is

$$\log\left(DollarVolume_{i,6Jul}\right) = \alpha + \delta \hat{S}_i^{bn} + \lambda \log(ADV_i) + \phi Loan_i + u_i.$$

Here $\hat{S}_i^{bn}$ is model-implied sale dollars in USD billions. Neither treatment nor outcome is divided by ADV. A complementary partial-rank test residualizes log event-day dollar volume with respect to log ADV and the loan indicator, then computes Spearman correlation with model-implied sale dollars.

The denominator-light specification separates scale from the modeled funding allocation. Raw predicted sales are highly related to incumbent size, and event-day dollar volume is highly related to ordinary dollar volume. Entering log ADV as a separate covariate tests whether predicted sale dollars explain execution-day quantity beyond a multiplicative capacity benchmark. The partial-rank test evaluates the same relation using residual ranks.

3.3 Mechanism outcomes

The mechanism analysis replaces the primary outcome with three measures: a final-hour volume z-score, the log ratio of final-hour volume share to its benchmark, and the 6 July market-model abnormal return. The first two ask whether the cross-sectional quantity relation is concentrated in a coarse closing-hour window. The third tests whether high-pressure securities have a different daily price response.

I also estimate the primary relative-volume model on 7 July and a stacked two-day model with a pressure-by-7-July interaction. The next-day coefficient tests persistence in the same stock cross section. The interaction

tests directly whether the pressure slope decays from the implementation session to the effective-date session, using stock-clustered inference for the paired two-day panel.

3.4 Date-placebo and component tests

For each trading day from 1 May through 8 July, I replace the 6 July outcome with that day's log volume relative to a fixed 1–25 June normal-volume baseline and re-estimate the same 93-stock regression with the same two controls. The 38 dates through 25 June are pre-announcement placebos under that fixed-baseline convention. The event's exact empirical rank among those placebos and 6 July supplies a date-level test that does not treat stocks as independent event realizations. Section 3.5 then replaces the fixed baseline with a strictly lagged design.

Pressure combines two components: predicted sale dollars and inverse trading capacity. To show that neither component alone mechanically creates the coefficient, I standardize log predicted sale dollars and negative log pre-event ADV and enter them jointly with the loan indicator. The joint regression is a decomposition of the cross-sectional ranking, not a substitute for the portfolio-arithmetic pressure measure.

3.5 Strictly lagged dynamic controls

The fixed-baseline placebo preserves an identical cross section and regression across dates, but it uses the June 1–25 normal-volume estimate for every outcome date. I therefore add a pseudo-real-time audit in which every date is treated as if it were the event. Relative volume is measured against the preceding 20 trading sessions. Realized return volatility, cumulative return, and the coefficient of variation of volume are also constructed only from those same lagged sessions and standardized within date. The full specification adds these three variables to log pre-event ADV and the loan indicator.

The dynamic placebo period begins only when all 93 securities have 20 complete lagged sessions. This yields 19 fully controlled pre-announcement dates from 29 May through 25 June. No event-day or future observation enters an outcome denominator or control. The sequence from the base dynamic model to volatility, momentum, and volume-variability controls is fixed and reported in full.

4 Results

4.1 Execution-day quantity response

The capacity-scaled coefficient is 8.6323 with HC3 standard error 2.0620 and $p = 0.0000283$. Multiplying by the cross-sectional standard deviation of pressure gives 0.1143 log points. Exponentiating implies a 12.1 percent increase in 6 July volume relative to normal for a one-standard-deviation increase in pressure.

The nonparametric pattern is visible across quartiles. Mean and median relative volume rise from the lowest-pressure group toward the highest-pressure group. The regression uses continuous pressure and the complete control set; the quartiles display the economic ordering.

Median event-day volume relative to normal rises from 0.721 in the lowest-pressure quartile to 0.841, 0.865, and 0.951 in the second through fourth quartiles. Mean relative volume rises from 0.744 to 0.853, 0.995, and 1.004. Thus both location measures order the four groups monotonically. The highest-pressure quartile trades approximately at its normal volume on average, while the lowest-pressure quartile trades about one quarter below normal; the cross-sectional funding allocation explains part of that gap.

Table 2 Main quantity and denominator results

Specification or diagnostic	Estimate	Inference
Capacity-scaled pressure	8.6323	HC3 SE 2.0620; p = 0.0000283
One-standard-deviation effect	0.1143 log points	Approximately 12.1% higher relative volume
Freedman-Lane test	—	20,000 draws; p = 0.000150
Pairs bootstrap	—	95% interval [4.743, 12.669]; 100% positive
Leave one out	8.077 to 9.367	Maximum p = 0.000135
Raw sale dollars, baseline denominator-light diagnostic	1.6939 per USD 1bn	HC3 SE 0.8622; p = 0.0495
Partial rank relation	rho = 0.2607	p = 0.0116

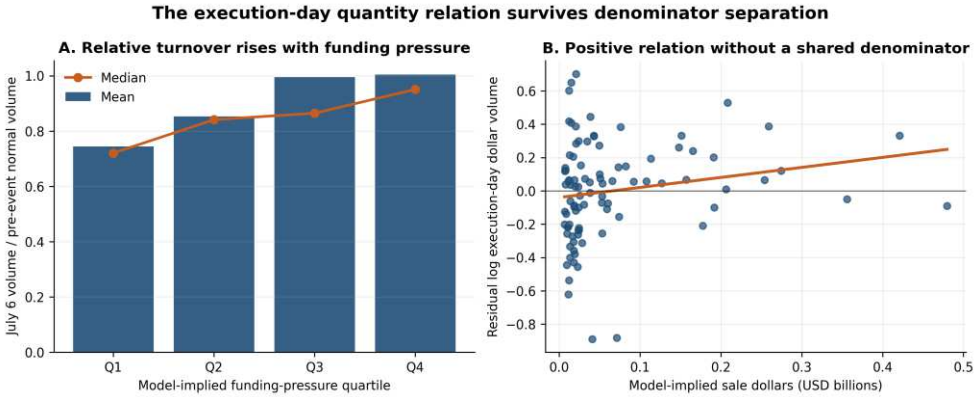


Figure 1. Panel A shows relative volume by model-implied funding-pressure quartile. Panel B reports the baseline denominator-light diagnostic after removing log pre-event ADV and loan status. The stricter dynamic-control audit is reported separately because it changes the information set and the interpretation of this diagnostic.

4.2 Execution-day timing and next-day decay

The pressure slope is concentrated on the 6 July implementation session. Re-estimating the relative-volume model on 7 July produces a coefficient of 3.4249 with p = 0.164. In the stacked two-day model, the pressure-by-7-July interaction is -6.0506 with a stock-clustered p-value of 0.0107. The change in slope is therefore statistically significant even though the two daily cross sections contain the same 93 securities.

This timing test rules out a simple interpretation in which high-pressure securities are merely stocks with persistently elevated contemporaneous volume. A fixed stock characteristic would tend to produce similar slopes on adjacent sessions. Instead, the relation is strongest on the session when tracking portfolios must prepare for the new composition and decays after implementation.

The broader date-placebo distribution is even more discriminating. Across 38 pre-announcement trading dates, estimated pressure coefficients range from -5.206 to 6.017. The 6 July coefficient of 8.632 is larger than every placebo coefficient and has an exact upper-tail rank p-value of 1/39, or 0.0256. Its HC3 p-value on the event date is 0.0000283. The contrast shows that the result is not a generic daily relation between the pressure ranking and turnover.

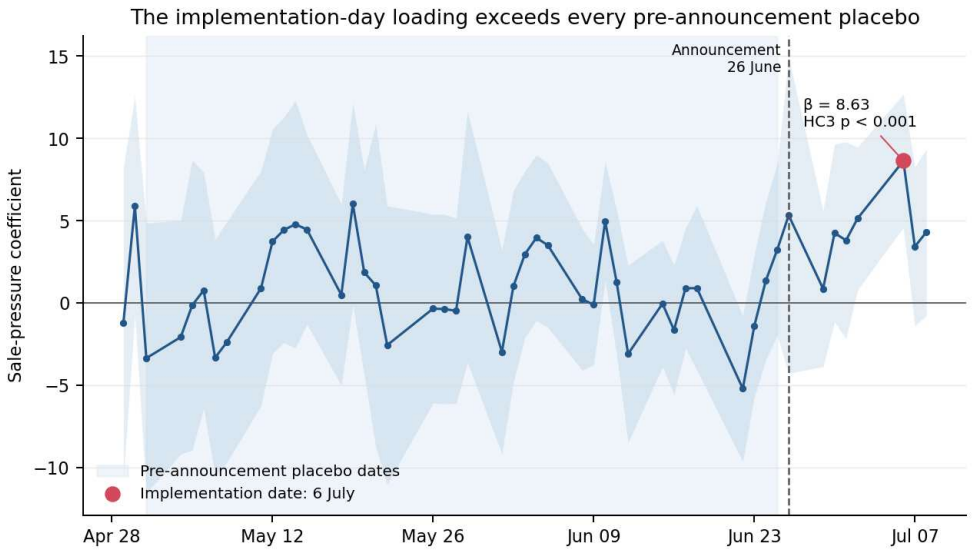


Figure 2. The line reports the sale-pressure coefficient from the same 93-stock regression on each date; shading gives pointwise 95 percent HC3 intervals. The 6 July implementation estimate exceeds all 38 pre-announcement placebos from 1 May through 25 June.

Table 3 Execution-day concentration

Test	Coefficient	Robust inference
6 July: pressure to log relative volume	8.6323	p = 0.0000283
7 July: pressure to log relative volume	3.4249	p = 0.1638
Pressure × 7 July decay interaction	-6.0506	Stock-clustered p = 0.0107

4.3 Strictly lagged dynamic-control audit

The pseudo-real-time construction confirms the event concentration without using a future or same-day normalization window. With only log ADV and loan status, but with relative volume recomputed against each date's preceding 20 sessions, the event coefficient is 7.3613 (p = 0.00017). It exceeds all 20 available pre-announcement placebo coefficients, giving an exact rank p-value of 1/21, or 0.0476.

Adding lagged realized volatility lowers the event coefficient to 6.2683 (p = 0.00282); adding lagged momentum gives 5.6934 (p = 0.0217); and the full model including lagged volume variability gives 6.0711 (p = 0.00798). The full-model coefficient corresponds to 0.0799 log points, or 8.3 percent higher relative volume per standard deviation of pressure. It remains larger than every one of the 19 fully observed placebo coefficients, whose maximum is 2.3125.

Table 4 Dynamic-control sequence

Specification	Event coefficient	HC3 p	Placebo dates	Event rank	Exact rank p
Lagged relative volume; ADV and loan controls	7.3613	0.00017	20	1 of 21	0.0476
Plus lagged realized volatility	6.2683	0.00282	19	1 of 20	0.0500
Plus lagged momentum	5.6934	0.0217	19	1 of 20	0.0500
Plus lagged volume variability	6.0711	0.00798	19	1 of 20	0.0500

4.4 Denominator separation

The baseline denominator-light coefficient is 1.6939 per USD 1 billion, with HC3 standard error 0.8622 and p = 0.04946. Because the dependent variable is in logs, the local semi-elasticity implies that an additional USD 100 million of model-implied sales is associated with approximately 0.169 log points more execution-day dollar volume, conditional on pre-event ADV and loan status.

The residual rank relation is positive (rho = 0.2607; p = 0.01159), showing that shared ADV scaling does not mechanically generate the baseline relation. The raw-dollar slope becomes imprecise when richer trading-state controls are added: its p-value is 0.134 with lagged realized volatility and 0.492 with the full dynamic control set. The capacity-scaled measure, which combines predicted burden with ordinary trading capacity, carries the stable inference.

The joint component regression further separates the numerator and capacity channels. Standardized log predicted sale dollars has coefficient 0.2132 (HC3 p = 0.0077), while standardized negative log ADV has coefficient 0.2582 (p = 0.0034); both are positive in the direction implied by pressure. Their correlation is -0.880 because large index weights tend to belong to liquid securities, making the joint test demanding. The result is therefore not produced solely by the largest predicted sales or solely by low ADV.

Table 5 Date and component falsification tests

Test	Estimate	Inference
6 July event coefficient	8.6323	HC3 p = 0.0000283
Pre-announcement placebo range	-5.206 to 6.017	38 trading dates
Event rank among placebos plus event	1 of 39	Exact upper-tail p = 0.0256
Standardized log predicted sales	0.2132	HC3 p = 0.0077
Standardized negative log ADV	0.2582	HC3 p = 0.0034

4.5 Randomization and influence

The 20,000-draw Freedman-Lane p-value is 0.000150. The pairs-bootstrap 95 percent interval is [4.743, 12.669], and every bootstrap coefficient is positive. Across 93 leave-one-out regressions, the coefficient ranges from 8.077 to 9.367 and the largest p-value is 0.000135. No security determines the primary relation.

4.6 Intraday location and price response

Funding pressure does not predict the final-hour volume z-score: the coefficient is 1.426 with p = 0.875. It also does not predict the log final-hour share ratio: the coefficient is 0.346 with p = 0.865. The available hourly measures therefore place the quantity response in full-day turnover rather than a detectable cross-sectional concentration in the last hour.

The 6 July market-model abnormal-return coefficient is -0.0575 with p = 0.737. The event therefore produces a strong pressure-ranked turnover gradient without a corresponding daily abnormal-return gradient, consistent with liquidity absorption in the available data.

A post-event price test gives the same pattern. Pressure does not predict the 8–13 July QQQ-adjusted reversal; the coefficient is -0.180 with HC3 p = 0.653. The measured response is a sharply allocated turnover increase, with no pressure-ranked daily price concession or reversal over the available horizons.

5 Economic Interpretation

The financing burden of an index addition is not evenly distributed in economic terms. Large-weight incumbents supply more dollars, while low-ADV incumbents face a larger burden for a given number of dollars. The capacity-scaled measure combines those dimensions and strongly orders implementation-day relative turnover.

The dynamic-control result clarifies the mechanism. Pressure continues to order event-day volume after recent volatility, momentum, and volume variability are measured strictly before every comparison date. The raw-dollar diagnostic shows that the baseline result is not a literal ratio identity, while its attenuation under richer controls confirms that the economically sharper object is predicted burden relative to ordinary capacity.

The absence of a final-hour gradient is compatible with pre-trading, continuous-session execution, derivatives, and dealer inventory before the closing benchmark. The data identify the incumbent quantity response but do not separate those execution channels. For index providers and portfolio managers, entrant size and incumbent liquidity jointly indicate where implementation capacity will be demanded.

The result also separates aggregate funding from local capacity. Predicted sale dollars are largest for high-weight incumbents, but pressure can be high for a smaller constituent when its ordinary dollar volume is low. A rebalance plan that uses weights alone therefore misses where execution is large relative to market capacity. The ratio measure is a natural first-pass map for order slicing, crossing opportunities, and dealer balance-sheet allocation.

The component regression shows why capacity scaling matters. Predicted sale size and inverse ADV both enter positively when modeled jointly, whereas raw predicted dollars become imprecise after recent trading-state controls are added. The combined burden-to-capacity map captures the stable event response.

For market design, the absence of a close-hour concentration is informative. Participants can pre-position, use futures or exchange-traded products, cross blocks, or internalize flow throughout the session. The full-day measure captures the aggregate absorption margin; finer order and venue data can separate the intraday execution channels.

6 Conclusion

SpaceX’s Nasdaq-100 entry created a common funding event with heterogeneous predicted burdens across incumbent securities. Model-implied funding pressure strongly orders 6 July relative turnover. A one-standard-deviation increase corresponds to 12.1 percent more implementation-day volume, with stable HC3, randomization, bootstrap, and leave-one-out inference.

The central result survives a strictly lagged specification that reconstructs normal volume and recent trading-state controls before every event and placebo date. The full dynamic coefficient is 6.071, its HC3 p-value is 0.0080, and the implementation date ranks first among the 19 fully controlled placebos plus the event. Coarse final-hour and daily abnormal-return tests are insignificant, locating the observable response in full-day quantities.

The timing evidence sharpens that conclusion. The pressure slope is 8.632 on 6 July, exceeds all 38 clean pre-announcement placebos, then falls to 3.425 and becomes insignificant on 7 July; the -6.051 decay interaction is significant at 1.1 percent. Together with the 20,000-draw cross-sectional randomization p-value of 0.000150 and the exact date-rank p-value of 0.0256, the results identify a strong, transitory implementation-day redistribution of trading activity.

This financing-side perspective yields a testable map for other large index additions: given a proposed entrant weight, incumbent weights, and pre-event liquidity, the model predicts which incumbents bear the largest burden relative to ordinary capacity. The SpaceX fast-entry event validates that map in one unusually large case. A historical panel using the same frozen construction is the next test of cross-event generality.

Declarations

Conflicts of interest

The author declares no competing financial or non-financial interests.

Data and code availability

The official event announcement is publicly available from Nasdaq. The replication package contains the processed 93-security cross section, pressure and denominator audits, timing and mechanism outputs, bootstrap and randomization summaries, and estimation code. Underlying licensed market data remain subject to their original provider terms; the processed variables, event definitions, identifiers, and source manifest needed to audit the reported analysis are included.

Use of generative AI

Generative AI tools were used for limited coding assistance and minor editorial support. All research design, analysis, interpretation, and final content were determined and verified by the author.

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