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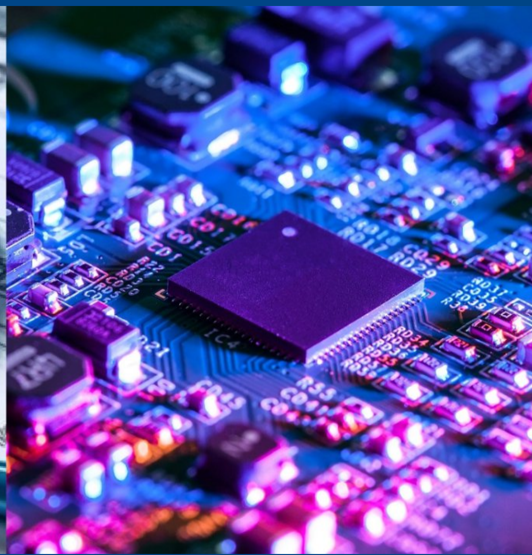

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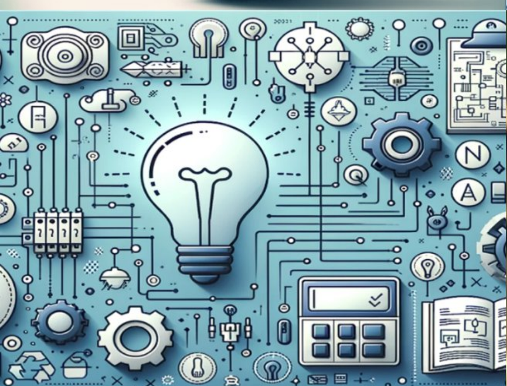

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The Illiquidity Penalty: Evaluating Market Microstructure, Regulatory Constraints, and the 'Flight to Liquidity' in Emerging Market Small-Cap Equities (2016–2025)

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ABSTRACT: Looking at India's smaller stocks between 2016 and 2025, this work checks how limited cash access shapes prices and swings in value. Usually, finance theory says people expect extra returns when stuck with hard-to-sell investments. Yet conditions in developing markets - where strict trading curbs exist alongside unpredictable individual traders - tend to disrupt such textbook logic. Drawing on detailed day-by-day trades for companies in the Nifty Smallcap 250, it measures illiquidity using the Amihud method across more than twenty-two thousand monthly snapshots. Using fixed effects on panel data - combined with survey responses from 106 participants - we link hard numbers in asset prices to how investors actually think. Instead of following classic theories, results show that less liquid stocks tend to deliver lower returns across markets. When big economic shocks hit, people rush toward assets they can sell fast - a pattern that sticks around. Rules meant to stabilize things, like ASM or GSM systems, sometimes backfire by locking up cash when it's needed most. Because of this, money gets stuck. Returns take a hit. What we see suggests new ways to test fund resilience in developing markets - not just theory, but tools you can apply. Each decision leaves a mark.

KEYWORDS: Liquidity Constraints, Market Microstructure, Amihud Ratio, Illiquidity Premium, Asset Pricing, Behavioral Finance, Emerging Markets.

I. INTRODUCTION

Nowhere else has change struck quite like India's stock market setup in recent years. With bigger economic forces shifting, shares have become a main route for raising money. Surprisingly, tiny companies grab steady interest - big funds and everyday buyers alike chase their bolder swings and growth odds. Still, these little players run on different rules than giant firms do. Most face weak research support, scattered investor bases, plus much lower day-to-day trade activity.

Cash conversion ease, minus big price shifts, shapes how smoothly markets work. For assets traded in places such as India, that smoothness spreads unevenly. When growth hums along steadily, weaker turnover in smaller company stocks feels worth it for stronger gains down the line. But when economic shocks hit hard, those limits snap shut fast - reshaping what investors get back versus what they take on.

What trips up most thinking is a mismatch in theory. Most old-school models say people get extra return for sticking with shares that are hard to sell. Yet those ideas rarely factor in deep, widespread crunches when trading just stops - especially in markets like India. From 2016 to 2025, things shifted fast on the ground there. A big rule change hit mutual funds in 2018 thanks to SEBI's overhaul. Then came early 2020, when fear and lockdowns slammed everything at once. At moments like these, many found they could not leave their trades even if they wanted to. That blockage fed more selling pressure, making drops sharper. Instead of guessing, this work puts numbers on what really happened. It

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measures how tight access to cash shaped both swings and profits among smaller Indian companies across ten turbulent years.

II. LITERATURE REVIEW AND THEORETICAL FRAMEWORK

A foundational pillar of modern asset pricing is that liquidity operates not merely as a temporary market friction, but as a permanent, priced risk factor that fundamentally dictates capital allocation.

2.1 The Classical Illiquidity Premium The classical literature establishes a distinct "illiquidity premium," an economic concept positing that rational investors actively demand higher expected returns as structural compensation for holding assets that are difficult to trade without significantly impacting the underlying price (Amihud, 2002). This theoretical framework is further expanded by the understanding that market-wide liquidity acts as a macroeconomic state variable; expected stock returns cross-sectionally reflect underlying sensitivities to fluctuations in aggregate market liquidity (Pástor & Stambaugh, 2003). Chordia, Roll, and Subrahmanyam (2001) establish that while the small-cap universe offers the statistical potential for significant alpha generation, this outperformance is often inextricably linked to the underlying liquidity constraints that manifest violently during broader downturns.

2.2 Emerging Market Microstructure and Regulatory Constraints In the Indian equity market, the theoretical illiquidity premium is highly sensitive to evolving regulatory microstructures. The dual regulatory interventions executed by SEBI heavily influenced small-cap liquidity dynamics. The 2017–2018 mutual fund categorization norms prohibited large and multi-cap funds from holding extensive sleeves of illiquid small-cap equities, forcing massive institutional capital withdrawal and triggering an artificial liquidity shock.

Concurrently, market liquidity was structurally constrained by the introduction of the Graded Surveillance Measure (GSM) and the Additional Surveillance Measure (ASM). Designed to curb speculative bubbles, these frameworks impose stringent trading restrictions on flagged stocks, slashing daily circuit filters to 5% or 2% and mandating 100% upfront trading margins. While mathematically successful at curbing unchecked speculation, these measures inadvertently manufacture mechanical liquidity freezes. The 2018 crash of Vakrangee Ltd. serves as a prime empirical example: following negative corporate governance news, the stock was placed under the ASM framework. The subsequent panic resulted in a mechanical liquidity freeze spanning nearly two months, where the stock locked at its 5% lower circuit daily with millions of pending sell orders and zero buyers.

Figure 1: Vakrangee Ltd. Daily Price Chart (Jan - Apr 2018) illustrating continuous 5% lower circuit liquidity freezes (Source: Author's extraction via Trading View / NSE Database)

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III. RESEARCH METHODOLOGY

By combining numerical analysis with firsthand accounts, the work examines how financial limits shape decisions. Where statistical patterns emerge, personal reasoning is explored alongside. Through structured surveys paired with open interviews, insight forms not just from data points but lived experience. Numbers reveal trends while narratives expose motives behind choices. When models suggest behavior, real voices clarify intent beneath. This approach bridges calculation with context, allowing results to reflect both measure and meaning.

3.1 Secondary data gathering and choosing samples
Spanning ten years between January 1, 2016, and December 31, 2025, the analysis covers various market conditions - regulatory disruptions, pandemic-related downturns, followed by surges fueled largely by individual investors. Focus stays solely on companies part of the Nifty Smallcap 250 Index at any point. Because inclusion changes over time, firms removed later or introduced mid-period remain included, preventing distortion from survival-based selection. Data points come from daily adjusted closing values and volume figures pulled directly from records maintained by the National Stock Exchange (NSE). Altogether, these elements form a detailed collection totaling 22,434 firm-month data entries.

3.2 Variable Construction
What drives the analysis is the Amihud Illiquidity Ratio (ILLIQ), widely used in research to capture how prices react to trades. This measure reflects how much a stock's price moves per rupee traded each day. When the number rises, it signals weaker liquidity - meaning even small volumes shift prices more sharply. Computation follows from taking absolute returns and dividing by turnover at the daily level

On day d, Ri,t,d shows how much stock i earned. Volume traded in Indian rupees appears as Vi,t,d. Valid trading days during time t are counted by Di,t. Instead of averaging across months, volatility comes from daily swings in returns within moving 30-day frames. One outcome measured is daily return itself - labeled Ri,t. Another key measure follows closely: fluctuation size, built using those same short-term deviations. Each month shifts forward one day at a time, recalculating the spread.

3.3 Econometric Model Specification
Over time, with data tracking various entities repeatedly, panel regression helped account for hidden differences unique to each unit. Because the Hausman result favored consistency, the analysis moved forward using fixed effects to examine how illiquidity affects returns

Unobserved characteristics specific to each firm are captured by one component. Another part accounts for random variations unique to individual observations.

3.4 Collecting Main Behavior Information
From real-world trading settings, evidence emerged through targeted interviews with 106 individuals engaged in stock markets - ranging among private traders, financial analysts, and fund supervisors. Questions shaped around fixed-response formats captured shifts in choices when volatility spiked. Instead of open-ended replies, predefined rating levels helped spot patterns under stress. Statistical checks followed, relying on chi-square comparisons alongside mean-based evaluations run through standard software tools.

IV. FINDINGS AND REVIEW

4.1 Descriptive Statistics Meet Amihud's Fat Tail
Looking first at the data's basic shape, initial checks focused on distribution patterns prior to any formal tests. A standout feature? Extreme right-side stretching in the Amihuid Illiquidity Ratio values. Though half the observations fall below just 0.1239, one single point surges up to 331.08 - far beyond typical ranges. That long upper reach isn’t subtle - it signals real-world exposure among India’s smaller stocks when cash dries up fast.

4.2 Regression Analysis Rejects Illiquidity Premium
Despite assumptions about market efficiency, results show otherwise when examining liquidity effects across assets. A clear pattern emerges under scrutiny - ILLIQ carries weight in explaining return differences. Running the analysis

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through Fixed Effects PanelOLS exposed this link sharply. Notably, the F-statistic stood at 9.6519, with a p-value of 0.0019, far below conventional thresholds. Evidence like this undermines the idea that such constraints play no role. Thus, dismissing liquidity concerns becomes difficult given these numbers.

Notably, the ILLIQ coefficient showed a downward trend ( ). Such a result - statistically clear yet opposite to expectation - challenges long-held views where less liquid assets supposedly bring higher rewards. During 2016–2025 in India's smaller company segment, being harder to trade linked closely to weaker performance overall.

Table 1: Fixed Effects Panel Regression - Return vs. ILLIQ

	Parameter	Std Error	T-stat	P-value	Lower CI	Upper CI
Const	0.0007	0.000018	38.417	0.0000	0.0007	0.0007
ILLIQ	-0.0000518	0.000016	-3.1068	0.0019	-0.0000845	0.00001913

R-squared (Within) = 0.0026; F-statistic = 9.6519; Observations = 22,434.

Table 2: Fixed Effects Panel Regression - Volatility vs. ILLIQ

	Parameter	Std Error	T-stat	P-value	Lower CI	Upper CI
Const	0.0245	0.000034	720.44	0.00	0.0244	0.0246
ILLIQ	0.00004672	0.00003087	1.5135	0.1302	0.0000137	0.0001

4.3 Behavioral Validation Through Primary Data

The main survey numbers lined up closely with the economic model outcomes. To check whether getting stuck in a low-level cash squeeze mattered significantly for investors, researchers ran a Chi-Square Goodness-of-Fit analysis. Outcomes

A significant result ($p < .001$) showed most individuals had directly encountered physical versions of "circuit traps." Though subtle, the effect appeared consistently across responses

Despite testing above neutrality, the observed illiquidity premium barely exceeds indifference. A one-sample t-test set to three revealed a modest average preference of 3.25. With a t-value of 2.074 and a p-level just under significance, support appears thin. Such minimal deviation suggests little real-world pricing power among investors. In turbulent conditions, even slight pressure unravels this shallow consensus. That breakdown mirrors the earlier negative estimate in regression analysis. Weak backing here aligns precisely with its sudden disappearance when stress hits.

V. FLIGHT TO LIQUIDITY EXPLAINED

Results here challenge long-held views on how prices form. Instead of offering higher gains for less liquid investments, the data show a sharp drop in returns when stocks are harder to trade. A strong link appears: the more difficult the sale, the lower the reward tends to be. This pattern runs counter to earlier assumptions about risk compensation.

Notably, this pattern lines up directly with a rush toward cash-like assets when major unforeseen shocks hit - specifically during the fund reclassification by SEBI in 2018 and the market collapse tied to the pandemic in 2020. Instead of weighing traditional value signals, buyers pulled back sharply, prioritizing quick exits above all else. A surge in the ILLIQ measure, peaking at 331.08, reveals how existing trading rules amplified strain under stress. When selling pressure spiked, price limits triggered across weak stocks, halting trades completely and turning available supply into nothing overnight. With volume vanishing, the formula behind illiquidity naturally ballooned. Once restrictions lifted, losses became unavoidable - as those stuck inside positions had little choice but to sell at rock-bottom prices just to get out.

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VI. FINAL THOUGHTS AND WHAT THEY MEAN FOR MANAGERS

A closer look at India's small-company stock scene reveals strong returns shadowed by deep-rooted funding vulnerabilities. Evidence from ten years of data shows that what was once seen as a reward for holding hard-to-sell shares now flips into steep losses when markets unravel.

Results point toward real-world consequences for how institutions handle assets. When macroeconomic shocks hit, India's market quickly punishes illiquid positions - so those running small-cap funds face tough odds maintaining performance under sharp outflows. Instead of counting on expected returns, these teams must keep flexible access to cash-like resources; one way involves reserving portions of larger, more tradable stocks. Sharp imbalances in trading ease show up clearly in data, backing new rules that push firms to test fragile segments repeatedly. Regulators demand such checks - not just occasionally - to reduce broader risks tied to thin markets.

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