Rethinking Volume: The Illusion of Liquidity*

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Abstract

We document a striking fact: While gross trading volume has increased fivefold since 1980, net volume – trading from persistent portfolio reallocations, which excludes transitory round-trip trades – has remained largely unchanged. Our evidence suggests that the rise in transitory round-trip trades is driven primarily by high-frequency intermediation. While this activity has enhanced high-frequency liquidity, it has not materially changed long-term liquidity. Consistent with the widening gap between gross and net trading volume, we find that high-frequency liquidity measures have significantly improved, while long-term price impact and mean reversion have remained largely unchanged over the past four decades. In a variety of cross-sectional applications, we further demonstrate that net volume better captures long-term liquidity than gross volume. Together with the stability of net volume, this corroborates our argument that long-term liquidity in the U.S. equity market has not meaningfully improved since 1980.

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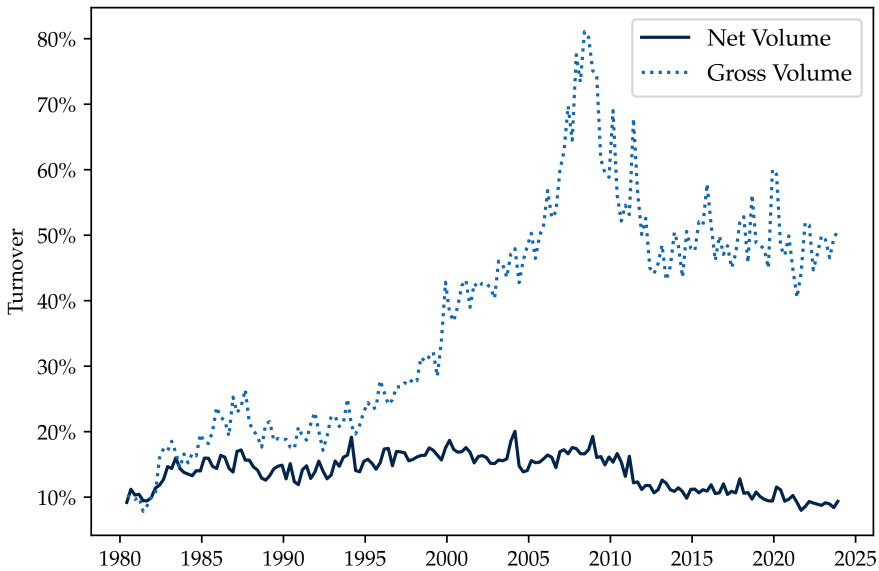
1 Introduction

Over the past four decades, gross trading volume in equity markets has risen sharply. In 1980, the average stock turned over about 40% of its shares outstanding per year; by 2000, turnover reached 100%, and by 2024 it exceeded 200%. In that year alone, total equity market trading volume amounted to roughly $92 trillion. This has led to the widespread notion that markets have become more liquid and efficient over time (Chordia et al., 2008). We document a striking fact: while gross trading volume has quintupled since 1980, trading volume associated with persistent portfolio reallocations, which we term *net volume*, has remained largely stable over time. Figure 1 plots median quarterly net and gross volume at the stock-level over the past four decades. Net volume is substantially smaller than gross volume – around 6–10% of shares outstanding per quarter – and the gap relative to gross volume has widened dramatically, from a factor of 2 to approximately 8.

Figure 1: **Gross Volume versus Net Volume for US Equities**
The figure plots quarterly gross trading volume, scaled by shares outstanding, against net trading volume, measured as the aggregate net portfolio reallocation inferred from changes in quarterly institutional holdings. Each series reports the cross-sectional median across U.S. stocks with at least 50% institutional ownership.



We show that the secular growth in gross trading volume relative to net volume is driven primarily by high-frequency round-trip trading, which may improve liquidity at very high frequencies, but does little to absorb persistent demand shifts over longer horizons. Consequently, and perhaps contrary to common belief, we find that equity markets have at best become more liquid at very high frequencies, while long-term liquidity has remained largely unchanged over the past decades.

To see the logic, consider a high-frequency trader who buys and sells several times within the same day. She generates high gross volume but zero net portfolio change at the daily frequency. While she provides intraday liquidity, she does not intend to hold positions overnight and therefore cannot accommodate persistent demand shifts. If a long-term investor wants to sell a given number of shares, she can provide liquidity in the short-term but must eventually pass the imbalance through to ultimate, long-term holders. Thus, long-term liquidity is more accurately reflected by "*net volume*": the total net portfolio reallocations within a given period, excluding transitory round-trip trades.

Consistent with the stability of net trading volume, we find that long-term price impact has remained largely unchanged from 1980 to 2024. In contrast, high-frequency price impact has declined systematically over the same period, as reflected, for example, in the narrowing of effective spreads. How can these two patterns be reconciled? Short-term price impact reflects transient liquidity effects that reverse over time toward the long-term impact. Over the past four decades, short- and long-term impact have systematically converged, leading to a steady decline in short-term price reversals. We argue that net volume, which reflects economically meaningful portfolio reallocations rather than high-frequency intermediation, is the superior measure of market liquidity at long horizons. We show that net volume fully subsumes gross trading volume in explaining long-term price impact in the cross-section of stocks.

We begin with a simple illustrative example based on a representative stock, showing how a portfolio reallocation by Fidelity and BlackRock can generate gross trading volume that far exceeds the net reallocation, as the trade is intermediated by several high-frequency traders. We then show how to systematically construct net volume and describe its properties. Net volume is the total trading induced by changes in portfolio holdings at a given horizon across all investors. The most comprehensive data on investor holdings comes from 13F filings, which are available quarterly. We therefore construct net volume as total quarterly trading activity inferred from 13F filings. As an alternative, we construct net volume using disaggregated S12 filings for mutual funds and ETFs; the results are unchanged. We scale all volume measures (gross and net) by shares outstanding. While this scaling technically corresponds to turnover, we use the simpler term "volume" throughout and explicitly indicate whenever we refer to unscaled measures.

We compare quarterly net volume to quarterly gross volume, obtained by summing daily gross trading volume within each quarter. In 1980, gross and net volume were comparable in magnitude. Today, gross volume is roughly eight times larger than net volume. This dispersion is not due to incomplete coverage in 13F data: even for stocks with over 95% ownership captured by 13F or S12 filings, the gap between gross and net volume remains just as large. Although the levels of the two measures diverge, they exhibit a high cross-sectional correlation of over 60%, which has remained stable over time. This suggests that gross and net volume capture similar underlying economic activity. However, we argue that gross volume is a considerably noisier measure of trading activity over a given horizon, as it is contaminated by cumulated high-frequency round-trip trades. We provide an intuitive example by showing that high-frequency trading firms Citadel and Jane Street, which reportedly intermediate over 30% of equity market volume, account for less than 1% of net volume. This finding echoes Menkveld (2013), who shows that a large high-frequency market maker participates in roughly 14% of all trades yet ends most stock-days with zero inventory.

Beyond individual examples, we provide novel, systematic evidence that round-trip trades implied by the gap between gross and net volume occur at very short horizons. Round-trip trading activity is strongly related to 15-second variance ratios, which alone explain a striking 60% of the cross-sectional variation in round-trip trading activity. Variance ratios at lower frequencies add little additional explanatory power. These results indicate that round-trip trading occurs at very high frequencies, making prices closer to random walks at those frequencies, but not at longer horizons. This finding is consistent with Chordia et al. (2005), who show that high-frequency trading eliminates intraday autocorrelation by accommodating order imbalances within 60 minutes.

Next, we examine the trends in long and short-term liquidity over the past 50 years. We begin with a simple qualitative argument based on trends in return volatility and trading volume at different horizons. A simple proxy for price impact is the ratio of return volatility to trading volume: when small amounts of trading generate large price movements, impact is high. Both daily and quarterly return volatility have remained largely unchanged over our sample period. In contrast, daily gross trading volume has increased systematically, while quarterly net volume has remained flat. Since 1980, the ratio of daily return volatility to daily trading volume has therefore declined sharply – from around 15 to 3 – while the corresponding quarterly ratio has remained remarkably stable at about 2.5. This pattern suggests that short-term price impact has fallen markedly, whereas long-term price impact has changed little, implying convergence between the two over time.

We then turn to formal empirical estimates of short- and long-term price impact over time. First, consistent with Chordia et al. (2008, 2011); Menkveld (2013) and the rise in gross volume, we confirm a substantial improvement in high-frequency liquidity over time. The median effective spread across stocks declines from about 8% in 1992 to around 1% in 2024. Similarly, five-minute price impact estimated from signed order-flow regressions falls by roughly a factor of four.[1] In contrast, and consistent with net volume remaining flat over time, we show that the long-run price impact of plausibly exogenous demand shifts has not materially changed. Using rolling regressions of quarterly returns on unexpected flow-induced trades, we find that the estimated price-impact coefficient has remained stable since the 1980s. We obtain the same result when using reinvested dividend-payouts as an alternative demand shock. In both cases, price impact is virtually unchanged over time and shows no statistically significant trend.[2] We then reconcile the declining short-term impact and constant long-term impact by assessing reversal patterns across horizons. First, the returns to short-term reversal strategies – a measure of compensation for liquidity provision (Nagel, 2012) – have systematically declined over time, indicating a shrinking gap between short- and long-term price impact. We then conduct a unified and statistically powerful econometric test across all horizons. To this end, we construct variance ratios using abnormal returns at different frequencies. High-frequency variance ratios have systematically converged toward one, indicating a decline in mean reversion consistent with diminishing returns to short-term reversal strategies. In contrast, long-horizon variance ratios have remained largely unchanged since 1980. Taken together, these patterns suggest that the rise of and increasing competition in high-frequency intermediation have steadily compressed – though not fully eliminated – the transient component of price impact beyond its long-run level. Meanwhile, the magnitude of the long-run price impact itself appears to have remained stable. Finally, we turn to structural evidence using the asset demand system of Koijen and Yogo (2019). The long-term coliquidity matrix implied by the estimated demand elasticities has remained largely stable over time, suggesting that long-term price impact has not materially changed since 1980.

Our results suggest that equity markets have not become materially better at absorbing long-term shifts in demand. In other words, despite the growth of the financial sector (Greenwood and Scharfstein, 2013) and the rise of high-frequency intermediation, long-term liquidity has remained essentially unchanged over the past four decades. This is consistent with Menkveld (2013) and Duffie (2010, 2018), who argue that modern market makers – key drivers of the rise in gross relative to net

[1] Hendershott et al. (2011) finds that algorithmic trading improves liquidity in terms of narrower spreads and reduced adverse selection.

[2] Greenwood and Sammon (2025) document that the abnormal return associated with S&P 500 index inclusions has declined over time despite the growth of passive investing. Relatedly, Chinco and Sammon (2024) show that liquidity provision around index reconstitutions has improved. However, this does not imply that the total price impact of index-related demand has diminished. Instead, the apparent disappearance of the index effect may reflect intertemporal shifting of price pressure – due to anticipation and front-running – rather than a reduction in aggregate price impact.

volume – are highly effective at redistributing risk but do not bear it over long horizons.[3]

To corroborate our claim that long-term price impact has remained unchanged, we benchmark net volume against gross volume in three widely used cross-sectional applications. This comparison provides an indirect test of long-term liquidity. If net volume outperforms gross volume as a liquidity proxy in the cross-section, its stability over time suggests that long-term liquidity has remained constant.

We first examine whether net volume explains cross-sectional variation in long-term price impact of demand shocks. If net volume governs long-horizon liquidity, long-term price responses should be larger for stocks with lower net volume. We test this prediction by interacting flow-induced and dividend-induced trades with past average net and gross volume.[4] When considered separately, both higher net volume and higher gross volume are associated with significantly lower price impact. When included jointly, however, net volume fully subsumes the effect of gross volume. In other words, long-term price impact in the cross-section of stocks is driven by net volume: the additional round-trip trades reflected in gross volume provide no incremental explanatory power at longer horizons.

Second, we examine the relationship between net volume and liquidity at high frequencies. Strikingly, despite being a slow-moving, quarterly measure, net volume significantly explains cross-sectional variation in both effective spreads and five-minute price impact even after controlling for gross volume, volatility, size, and high-frequency order imbalance volatility (Bogousslavsky and Collin-Dufresne, 2023). Net volume matters even at these high frequencies because liquidity provision is inherently intertemporal. Market makers price trades based on their expected ability to unwind positions, which depends on the willingness of future investors to absorb order flow. This willingness is determined recursively across investor horizons and ultimately pinned down by long-horizon investors' willingness to reallocate their portfolios: Net volume. As a result, net volume contributes to liquidity at all horizons, including very high frequencies, and is a relevant complement to gross volume for measuring high-frequency transaction costs.

Third, we show that net trading volume contains incremental information for return predictability beyond gross volume in the cross-section of U.S. stocks. Without taking a stance on whether volume

[3]Similarly, Hendershott and Menkveld (2014) document short inventory half-lives for NYSE intermediaries, ranging from hours for large-cap stocks to at most two days for small caps.

[4]A large literature uses flow- and dividend-induced trades to estimate the *size* of equity market multipliers (Lou, 2012; Li and Lin, 2022; Chaudhary et al., 2023; Schmickler and Tremacoldi-Rossi, 2022; Hartzmark and Solomon, 2021; Chaudhry and Li, 2025; Kvamvold and Lindset, 2018). We are less concerned with the absolute size and more with the evolution over time and the heterogeneity in the cross-section.

predicts returns through liquidity compensation or sentiment-driven mispricing, we find that stocks with lower net volume (or net-volume-based Amihud illiquidity) earn higher future monthly returns, and that incorporating net volume improves the explanatory power of standard volume-based measures.

Finally, we show how to construct net volume at the level of the aggregate stock market. A large literature measures aggregate trading volume as the sum of individual stock gross volume and uses it as a proxy for market-wide liquidity (Jones, 2002) or sentiment-driven demand shocks (Baker and Stein, 2004). A key limitation of this approach is that gross trading volume counts round-trip trades that do not reflect economically meaningful reallocations of capital into or out of the stock market. At the market level, round-trip trades arise both cross-sectionally, when investors rotate across stocks without changing aggregate equity exposure, and over time, when short-horizon market-timing trades offset within the return horizon of interest. We construct a measure of market-level net volume that nets out both types of round-trip trading and directly captures investor flows into and out of equities. Empirically, market-level gross volume has increased sharply since the 1980s, while market-level net volume has remained stable. By the end of our sample, gross market volume exceeds net market volume by an astonishing *factor* of 25. This difference implies that the aggregate stock market is much less liquid than suggested by gross trading volume and that even small flows into and out of the stock market can potentially generate high price impact, consistent with Gabaix and Koijen (2021). van der Beck et al. (2025) use our net volume measure to derive an explicit bound on price impact, conditional on investor disagreement.[5] Revisiting Jones (2002), we further show that gross volume no longer predicts market returns, whereas net volume robustly predicts future excess returns across horizons. These results suggest that net volume is the economically relevant measure for studying aggregate liquidity and sentiment-driven demand at longer horizons.

The remainder of the paper is structured as follows. Section 2 introduces net volume and identifies the frequency of round-trip trades that drive the gap between gross and net volume. Section 3 documents trends (and the absence thereof) in long- and short-term liquidity over time. Section 4 provides cross-sectional applications of net volume. Section 5 constructs net volume for the aggregate stock market. Section 6 concludes.

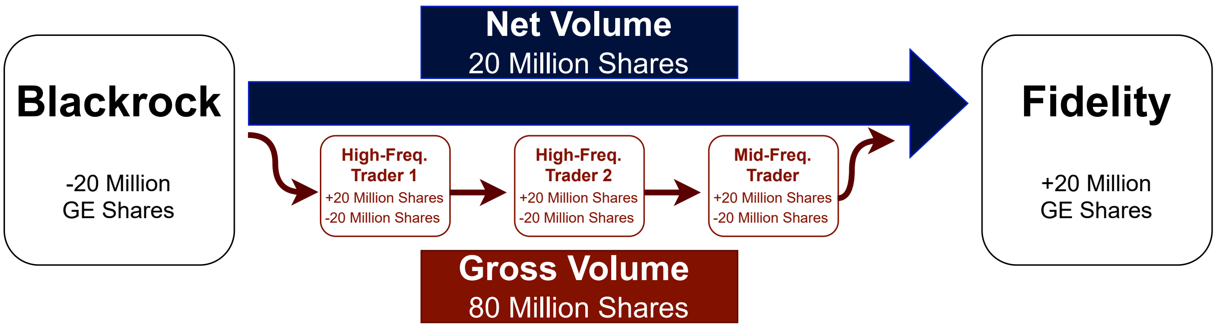
[5] Gabaix et al. (2025) study a related risk-transfer measure based on household portfolio reallocations.

2 Introducing Net Volume

2.1 An Illustrative Example

To set the stage, we present an illustrative example based on real data. We consider a randomly chosen stock-quarter pair: General Electric in the third quarter of 2014. On June 30, Fidelity reportedly held 105 million shares of GE. By September 30, Fidelity reported holdings of 125 million shares, an increase of 20 million. Over the same period, BlackRock's holdings decreased by roughly 20 million shares.[6] In total, all buyers jointly acquired about 190 million shares, which was matched by all sellers, including the imputed non-institutional sector. That is, based on reported holdings, approximately 190 million shares changed hands during the quarter. By contrast, reported gross trading activity, the total number of shares that exchanged hands over this quarter, was roughly 1 billion. Figure 2 illustrates the source of this divergence between gross and net trading activity, using the example of BlackRock and Fidelity.

Figure 2: **Illustrative Example**
The figure plots a stylized trade in General Electric between BlackRock Advisory and Fidelity, using rounded numbers based on their reported 13F filings as of June 30 and September 30, 2014.



When BlackRock sells 20 million shares over the quarter to Fidelity, the actual trading process is mediated by intermediaries. In practice, a high-frequency trader may first purchase the shares from BlackRock, hold them for a very short period, and then quickly sell them to another market maker. That intermediary may hold the shares somewhat longer before passing them on to yet another, perhaps mid-frequency, trader. Because none of these intermediaries end the quarter holding the shares, their trades are referred to as round-trip trades.

Clearly, this description is schematic. In our simple stylized setting, any trader who briefly holds some of the 20 million shares during the quarter but ends the period with zero holdings is classified as

[6] The fact that these quantities match exactly in this example is a convenient coincidence that simplifies the exposition.

a market maker. These intermediaries make the market between BlackRock and Fidelity and need not be high-frequency traders in the millisecond sense; from the perspective of long-term investors, even an intermediary who holds the shares for a few days plays the role of a market maker.

After several such round trips, the final market maker sells the shares to Fidelity, which holds the shares sold by BlackRock at the end of the quarter. In this example, three intermediating market makers generate gross trading volume four times larger than the underlying economic trade: a 20 million-share net transfer is transformed into 80 million shares of gross volume. More generally, the number of intermediating market makers varies across stocks, trades, and time periods, leading gross volume to range from only twice to several times the underlying net transfer. This variation introduces substantial noise into gross trading volume as a measure of the underlying economic trading activity between long-term investors such as BlackRock and Fidelity.

2.2 Data Sources

We use daily stock-level data and restrict our sample to common ordinary shares (share codes 10 and 11) traded on the NYSE, AMEX, and NASDAQ (exchange codes 1, 2, and 3).[7] Prices and fundamentals are from CRSP and Compustat. Intra-day liquidity measures from 2003 to 2024 are from the Trades and Quotes (TAQ) Daily Product. Prior to the decimilization period we use TAQ's Monthly product. We obtain quarterly institution-level and fund-level share holdings from 1980 to 2024 from the Thomson Institutional and Mutual Fund Holdings Databases respectively (s34 and s12 file). Because holdings are aggregated across funds within the same asset manager, we disaggregate 13F managers using S12 filings. We find that our empirical results are almost perfectly unchanged under this disaggregation, and therefore we rely on the simpler approach that aggregates 13F trades.[8]

2.3 Constructing Net Volume

Investors are indexed by $i = 1, \ldots, I$, stocks by $n = 1, \ldots, N$, and quarters by $t = 1, \ldots, T$. We construct net volume as the sum of trading activity from changes in reported portfolio holdings

$$\text{Net Volume}_t(n) = \frac{0.5 \sum_{i=1}^{I} |\Delta Q_{i,t}(n)|}{\text{Shrout}_t(n)} \tag{1}$$

[7] All results are robust to the subset of stocks that have (on average) at least 50% observed institutional ownership.
[8] Results using the disaggregated data are reported in the Appendix.

where $\Delta Q_{i,t}(n) = Q_{i,t}(n) - Q_{i,t-1}(n)$ is the (split-adjusted) change in the quantity of shares in stock n by institution i in quarter t. The factor of 0.5 corrects for double counting: since each trade between two investors enters the sum twice—once for each counterparty—dividing by two renders net volume directly comparable to CRSP's gross volume measure, which counts each trade once. Normalizing by shares outstanding technically yields a turnover measure; for simplicity, we continue to refer to it as volume. The raw number of shares traded has little economic meaning on its own. A more informative measure is Net Dollar Volume$_t(n) = 0.5 \sum_{i=1}^{I} |\Delta Q_{i,t}(n)| P_t(n)$, which aggregates trading activity in dollar terms using contemporaneous prices. Net dollar volume is equivalent to multiplying net volume by market equity. We include extensive margin trades, i.e., whenever an institution does not hold a stock at $t-1$ but holds it at t, and vice versa, we set the respective trades $|\Delta Q_{i,t}(n)|$ to $Q_{i,t}(n)$ and $Q_{i,t-1}(n)$ respectively. Because holdings are reported quarterly, net volume is by definition a quarterly measure.

Following Koijen and Yogo (2019), we treat residual shares outstanding not held by 13F institutions as a single residual sector (e.g., the household sector). Changes in firms' shares outstanding are therefore absorbed by this sector's $\Delta Q_{i,t}(n)$. Excluding the residual sector leaves all magnitudes and empirical results unchanged. Naturally, incomplete observability of holdings is an inherent limitation of portfolio data. In the next section, we verify that the omitted residual sector does not drive the divergence between net and gross volume. We also consider several alternative constructions of net volume (including disaggregating 13F managers using S12 data), excluding extensive-margin trades, and incorporating changes in short interest. All results and magnitudes remain qualitatively and quantitatively unchanged.

To understand why this is *net* volume, it is instructive to compare it to total trading volume, which we term *gross* volume. Quarterly *gross* volume aggregates total trading activity observed at higher frequency within each quarter. Let $V_d(n)$ denote daily share volume for stock n on trading day d (as reported by CRSP), and let $\mathcal{D}_t$ be the set of trading days in quarter t. Quarterly gross volume is defined as $\frac{\sum_{d \in \mathcal{D}_t} V_d(n)}{\text{Shrout}_t(n)}$. Similarly, gross dollar volume is defined as $\sum_{d \in \mathcal{D}_t} V_d(n) P_d(n)$. Net volume removes round-trip trades from investors who close out their positions within a quarter and is therefore strictly smaller than gross volume. To see this, consider an investor that moves from 1000 shares in quarter t to 1100 shares at $t + 10$days, back to 1000 shares at the beginning of the next quarter $t + 1$. While the investor's gross volume is 200 shares, their portfolio turnover from t to $t + 1$ is $|\Delta Q_{i,t}| = 0$ shares. To understand the liquidity provision at the quarterly frequency (here t to $t + 1$), the intra-quarter round trips are irrelevant and hence netted out from portfolio turnover.

Finally, note that net volume is conceptually similar to investor turnover as defined in Gaspar et al. (2005), which measures portfolio turnover at the institutional level and then computes, for each stock, the (weighted) average of institution-level turnover. Importantly, however, this measure differs from net volume. An institution may exhibit high overall portfolio turnover and hold a large position in Apple, yet never trade Apple itself. In that case, investor turnover for Apple would still be high, even though the institution's net volume in Apple is zero.

2.4 The Relationship of Net and Gross Volume

Table 1 provides summary statistics for net and gross volume from 1980 to 2024. Over the sample period, quarterly net volume has remained largely constant, both for all stocks and large-cap stocks and ranges between 6 and 10% of shares outstanding. In contrast, quarterly gross volume has more than tripled and now stands at 60% for the average large-cap stock.

Table 1: **Summary Statistics: Net versus Gross Volume**
This table reports summary statistics for net and gross volume by decade. Net volume is constructed from quarterly changes in institutional holdings, while gross volume aggregates total trading activity at the quarterly level. The sample spans 1980–2024. Large-cap stocks are in the top quintile of market equity in a given quarter. The bottom row reports the cross-sectional rank correlation across net and gross volume. Both net and gross volume are expressed as a fraction of shares outstanding.

(a) All Stocks

		1980	1990	2000	2010	2020
Net Volume	mean	0.060	0.078	0.107	0.099	0.105
	median	0.043	0.057	0.088	0.080	0.073
	IQR	0.055	0.075	0.104	0.080	0.069
Gross Volume	mean	0.178	0.305	0.489	0.531	0.627
	median	0.125	0.173	0.317	0.392	0.399
	IQR	0.156	0.267	0.504	0.453	0.443
CS Corr. ρ(Net,Gross)		0.466	0.551	0.703	0.692	0.539
TS Corr. ρ(Net,Gross)		0.155	0.162	0.242	0.211	0.199

(b) Large Cap Stocks

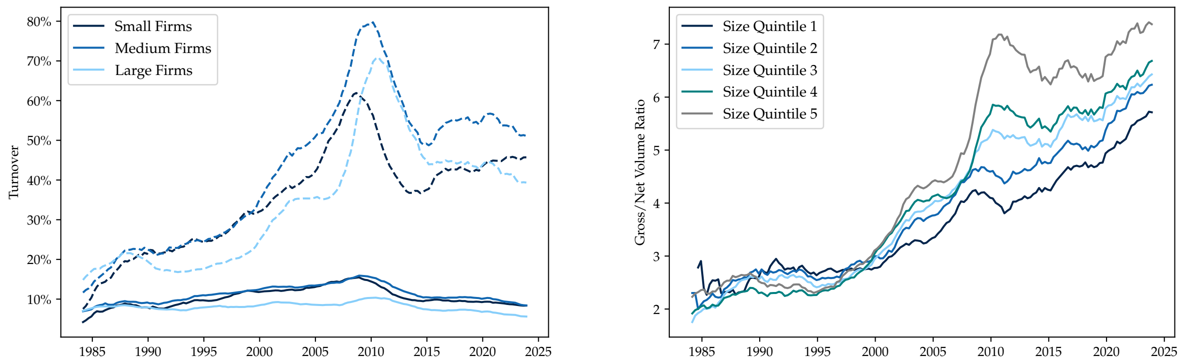
		1980	1990	2000	2010	2020
Net Volume	mean	0.074	0.093	0.116	0.095	0.076
	median	0.062	0.075	0.099	0.081	0.065
	IQR	0.049	0.067	0.075	0.059	0.043
Gross Volume	mean	0.192	0.318	0.629	0.610	0.600
	median	0.148	0.187	0.456	0.494	0.436
	IQR	0.128	0.207	0.491	0.364	0.321
CS Corr. ρ(Net,Gross)		0.518	0.643	0.641	0.675	0.664
TS Corr. ρ(Net,Gross)		0.175	0.122	0.184	0.195	0.235

The bottom row of the table reports the cross-sectional rank correlation between net and gross volume. Quite strikingly, the two measures are extremely highly correlated, with rank correlations of around 60–70%. This suggests that net volume and gross volume capture fundamentally similar objects. Even in the time series of individual stocks, the average correlation between gross volume and net volume is 15–30%. This suggests that institutional portfolio rebalancing and total trading volume capture a similar underlying phenomenon, but that trading volume is inflated by round-trip trades of high-frequency traders and other short-term investors.

Panel (a) of Figure 3 plots gross and net trading volume across the size distribution of U.S. stocks. The widening divergence between gross and net volume is present for firms of all sizes. Across the size distribution, gross trading volume has increased sharply while net trading volume, which captures economically meaningful portfolio reallocations, has remained flat. Panel (b) plots the ratio of gross to net volume by size quintile. The evolution of the ratio is remarkably similar across the entire size distribution and has increased monotonically over time for all firm sizes, rising from roughly 2–3 in 1990 to about 5–7 by 2024.

Figure 3: **Gross versus Net Volume Ratio by Stock Size**
Panel (a) plots median gross and net trading volume for small, medium, and large firms, defined as the first, third, and fifth quintiles of market capitalization. The solid and dotted lines indicate net and gross volumes respectively. Panel (b) plots the median ratio of gross to net trading volume for all size quintiles from 1980 to 2024.

(a) Gross and Net Volume Ratio by Size (b) Gross/Net Volume Ratio by Size



2.5 Missing Investors and Aggregated Holdings

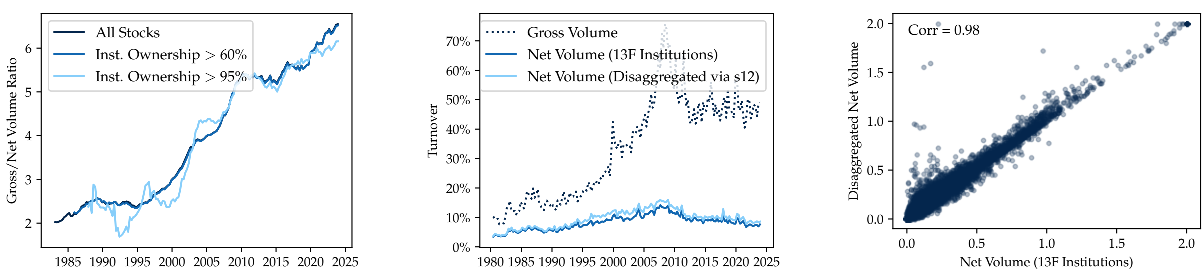
A possibility is that the gap between gross and net volume is actually a data artifact arising from omitted investors in the 13F data, rather than round-trip trades within the 13F data. Another possibility is that, because 13F data is aggregated at the manager level, it conceals substantial trading among affiliated funds within the same manager. We strongly confirm that neither explanation drives our results.

First, we verify that the gap between gross and net volume is not driven by large trades within the unobserved non-13F sector. Panel (a) of Figure 4 plots the ratio of gross trading volume to portfolio turnover for the full sample and for subsamples restricted to stocks with institutional ownership above 60% and 95%. The three series lie almost exactly on top of each other throughout the sample period, indicating that the divergence between gross trading volume and portfolio turnover is not driven by unobserved portfolio changes. Even for stocks that are almost entirely institutionally held, the gross-to-net ratio rises from roughly 2 to 6 over time. This rules out large, persistent offsetting reallocations in the non-13F sector (i.e., households and institutions with holdings below the 13F reporting threshold) as the source of the widening gap between gross and net volume. This is in line with Baker et al. (2007) who show that quarterly institutional portfolio turnover is much higher than retail turnover during stock-for-stock mergers.

Second, we verify that the gap between gross and net volume is not driven by aggregation across investors. In principle, large offsetting trades across mutual funds within a quarter could net out when holdings are reported at the asset-manager level in the 13F data, mechanically reducing measured net volume. At the limit, aggregating all institutions would yield zero net volume by construction. To address this concern, we disaggregate 13F asset-manager holdings (S34) using Thomson Reuters mutual fund holdings data (S12).[9] Panel (b) of Figure 4 reports the median net volume based on the disaggregated holdings. Net volume increases only marginally relative to the aggregated 13F measure, indicating that within-manager aggregation plays a negligible role. Panel (c) plots net volume from aggregated and disaggregated data. The two measures lie almost exactly on the 45-degree line and exhibit a correlation of 98%.

Figure 4: **Net Volume: Omitted Investors and Disaggregated Holdings**
Panel (a) of this figure plots the ratio of gross versus net volume for all stocks, stocks with institutional ownership above 60% and stocks with institutional ownership above 95%. Panel (b) plots median gross volume against net volume constructed from disaggregating 13F data using Thomson Reuters S12 mutual fund holdings files. Panel (c) is a scatter plot at the stock-quarter level of net volume constructed from 13F filings against net volume constructed from disaggregated data.

(a) Omitted Investors (b) Disaggregated Holdings (c) Corr. with Alternative



Overall, these results indicate that the growth in gross volume is entirely driven by higher-frequency round-trip trades, while long-term portfolio reallocations have not changed materially over time. Importantly, this evidence does not identify the exact frequency of these round trips – only that they

[9] Using the S12-S34 link table, we match mutual fund holdings to their corresponding asset managers in the 13F data. For asset managers whose total 13F holdings exceed the sum of their affiliated mutual fund holdings, we construct a residual entity capturing the difference. We retain 13F institutions that are not matched to any mutual fund and compute portfolio turnover from the merged dataset using the same methodology as in the main text.

occur at horizons shorter than the quarterly frequency at which holdings are observed. In principle, net volume could have increased at intermediate frequencies, such as monthly. The next section provides evidence against this possibility and shows that round-trip trading occurs at much higher frequencies, most plausibly intraday.

2.6 Identifying the Frequency of Round-trip Trades

Gross trading volume far exceeds net trading volume. Because this pattern holds even for stocks with nearly 100% institutional ownership, the gap must reflect round trip trades occurring at horizons shorter than quarterly rebalancing. At what frequency do these round trips occur? The precise horizon is not central to our argument. Our only requirement is that they take place within the quarter and therefore cannot provide liquidity to quarterly demand shifts. Nevertheless, the distinction is economically important. Round trips at microsecond horizons merely recycle intraday order flow and cannot absorb persistent imbalances, whereas round trips at weekly horizons can provide meaningful liquidity to daily demand shocks. In line with Hendershott et al. (2011), a substantial share of round trip trading likely occurs at very short horizons, often on the order of seconds. Because trades are anonymized, individual round trips cannot be directly observed. We therefore use return dynamics, a market outcome that reflects liquidity provision, to infer their frequency.

The key idea is that round-trip trading provides liquidity at its operating frequency but is less effective at absorbing demand imbalances that persist at lower frequencies. For example, a market maker active only intraday can facilitate intraday trades but cannot supply liquidity to overnight imbalances. By examining how round-trip trading relates to liquidity measures at different horizons, we can infer its average operating frequency.

$$\text{Round-trips}_t(n) = \ln(\text{Gross Dollar Volume}_t(n) - \text{Net Dollar Volume}_t(n)), \quad (2)$$

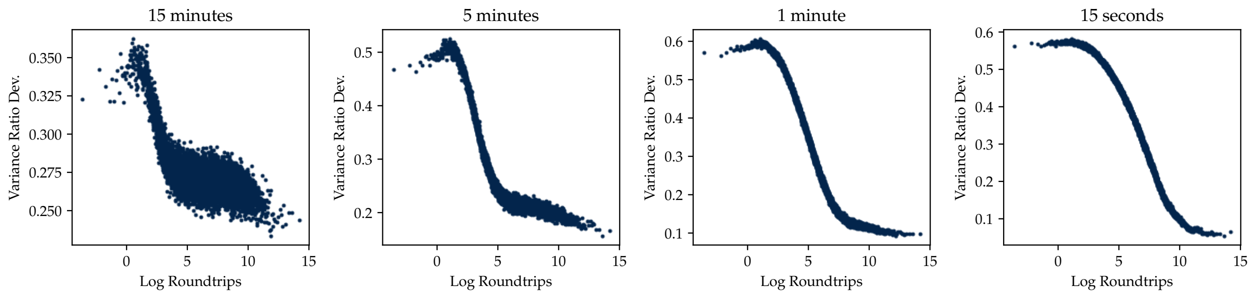
where *gross dollar volume* is the rolling 63-day sum of daily gross dollar volume and *net dollar volume* is the quarterly dollar net volume constructed from quarterly portfolio changes. In a frictionless market, abnormal returns follow a random walk. Illiquidity generates transitory price impact and thus return predictability. We proxy for deviations from random walk at different intraday frequencies using variance ratio deviations from the WRDS TAQ Intraday Indicators.[10] We then test whether round-

[10]Formally, for each stock-day, the variance ratio at frequency k is defined as $VR_k(n) = \frac{\text{Var}(r_{k,t}(n))}{k \cdot \text{Var}(r_t(n))}$. Under a random walk, returns are serially uncorrelated, so $VR_k(n) = 1$ for all k. Deviations from random walks are therefore given by

trip trading is related to these variance ratio deviations, and at which frequencies. Figure 5 presents binned scatter plots of variance ratios at different frequencies against round-trip trading. We consider frequency ratios of 15/5 seconds, 60/15 seconds, 5/1 minutes, and 15/5 minutes using intraday data from TAQ indicators.

A clear pattern emerges. At the 15/5 minute frequency, deviations from random walks disappear as round-trip trading increases, consistent with the liquidity-providing role of roundtrip trades. This relationship strengthens steadily at higher frequencies and is particularly strong at the 15/5 second horizon. Appendix Table C.1 reports the corresponding R^2 values from regressions of round-trip trading on variance ratios at different frequencies. The 15/5 second variance ratio alone explains about 60% of the within variation in round-trip trading, whereas the 15/5 minute ratio explains less than 1%.[11] The sharp drop in explanatory power at lower frequencies suggests that the excess trading captured by the gap between gross and net volume primarily provides liquidity at very high frequencies, with smaller effects at longer horizons.

Figure 5: **Round-Trip Trades and Variance Ratio Deviations**
The figure plots stock-day variance ratio deviations against round-trip trading, defined as the log difference between gross and net dollar volume. Each panel corresponds to a different frequency used to construct the variance ratio: 15/5 minutes, 5/1 minutes, 60/15 seconds, and 15/5 seconds. Variance ratios are measured as absolute deviations from a random walk $\left|\frac{\mathrm{Var}(r_{k,t}(n))}{k\cdot\mathrm{Var}(r_t(n))}-1\right|$. We bin roundtrip trading activity in 10,000 equal-sized bins and plot the average round-trip trading activity and variance ratio deviation per bin.



Several additional pieces of evidence corroborate that the large departure between gross and net volume is attributable to high-frequency trading. First, case studies of prominent high-frequency market makers show that they generate disproportionately large gross volumes while contributing very little net volume. Consider Citadel Securities, which publicly reports that it alone accounts for 23% of U.S. equity trading volume.[12] Similarly, Jane Street Capital reports that it accounts for 10.4%

$VRDev_k(n) = |VR_k(n) - 1|$. Table C.9 in the Appendix provides summary statistics on the variance ratio deviations at different frequencies.

[11]Notably, this is mere evidence on the frequency at which round trips occur. We do not interpret these regressions as establishing causality.

[12]See `https://www.citadelsecurities.com/what-we-do/equities/`, accessed on May 27, 2025.

of equity trading in the U.S.[13] We compute net volume for the largest US market makers that file quarterly holdings with the SEC, including Citadel, Jane Street, Virtu, and Two Sigma. Figure C.1 in the Appendix plots their joint share of net volume from 2011 to 2023. While Jane Street and Citadel alone account for over 30% of gross volume in the U.S., all of these market makers together account for less than 2% of net volume. Similarly, several studies using execution-level data document that high-frequency traders generate overwhelmingly large gross volumes at high frequencies with little to no low-frequency net volume; see, for example, Frazzini et al. (2018) for a quantitative asset manager and Menkveld (2013) for a high-frequency market maker.

Second, industry reports and academic studies document that high-frequency trading, or more broadly algorithmic trading, grew from virtually non-existent in the mid-1990s to 50%–70% of total volume in U.S.-listed equities by 2010 (Brogaard et al., 2014a; SEC, 2014; Hendershott and Riordan, 2013). The timing of the growth in algorithmic trading coincides with the widening gap between gross and net volume documented in Figure 1.

Overall, the evidence strongly suggests that the widening gap between gross and net volume is driven by round-trip trading at very high frequencies. Consequently, aggregating gross volume to lower frequencies substantially overstates economically meaningful trading at longer horizons and does not accurately capture liquidity provision at those horizons.

3 The (Absence of) Trends in Long-Term Liquidity

Our main argument is that the relative stability of net volume implies that long-term liquidity has not materially changed over time. In contrast, the growing divergence between gross and net volume suggests that trading activity at very short horizons—most plausibly high-frequency trading—has increased substantially. We document this contrast using 4 complementary approaches: a simple qualitative argument, direct estimates of price impact estimates from plausibly exogenous demand shocks, the mean reversion of stock returns implied from variance ratio tests at multiple horizons, and evidence from a structural model of long-term impact.

[13]See `https://www.bloomberg.com/news/articles/2024-04-17/jane-street-scores-10-6-billion-trading-haul-amid-growth-push`.

3.1 A Simple Qualitative Argument

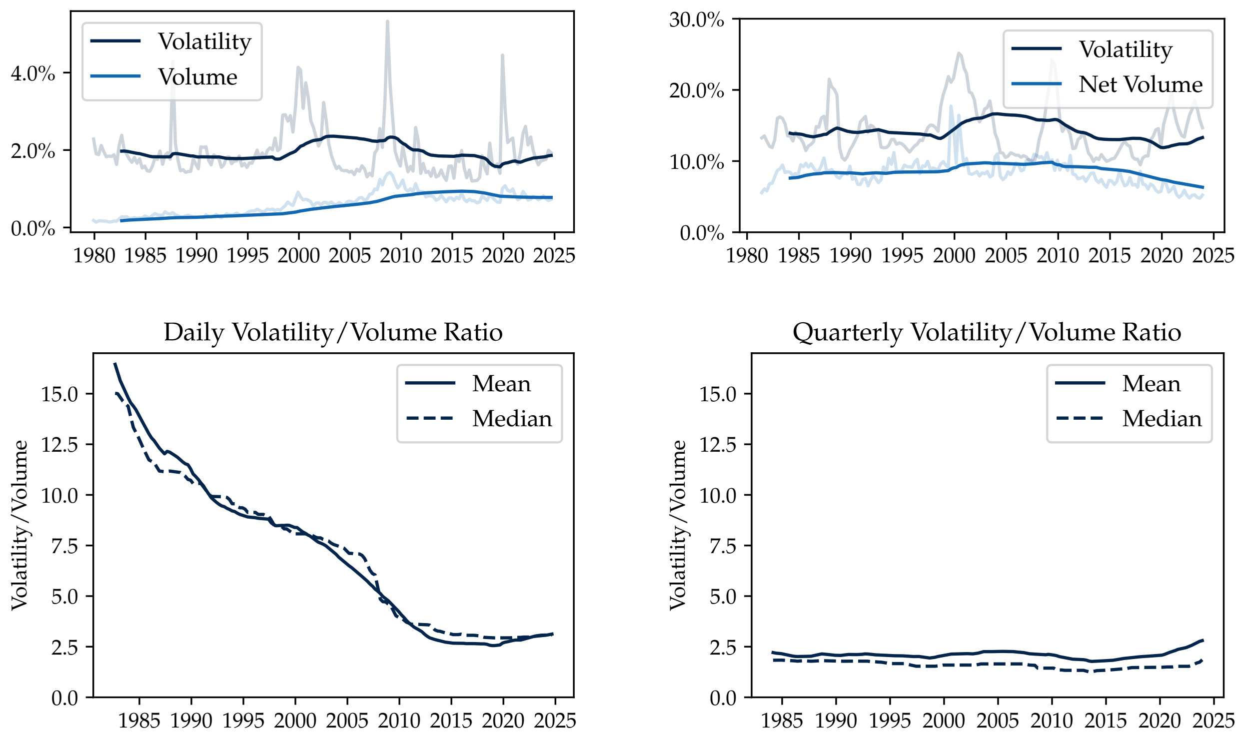
We set the stage with a simple qualitative argument. The ratio of return volatility to volume is a proxy for price impact. The intuition is straight-forward: when a given amount of trading volume generates a large amount of price volatility, prices are more sensitive to demand shifts, indicating higher price impact (Amihud, 2002; van der Beck et al., 2025).

Panel (a) of Figure 6 plots daily stock-level return volatility and daily trading volume (relative to shares outstanding). Daily volume has increased sharply over time from around 0.15% to 0.75% of shares outstanding for the average stock. Over the same period, return volatility has remained relatively stable at around 2%. As a result, the ratio of volatility to volume has declined steadily, falling from about 15 in 1980 to approximately 3 in 2024. Panel (b) plots quarterly stock-level return volatility and quarterly (net) trading volume constructed as shown in the previous section. Quarterly return volatility is approximately 15% and has also remained stable over time. In contrast to daily gross volume, however, quarterly net volume has remained largely flat at around 6%. Consequently, the ratio of return volatility to volume has also remained stable over time, at roughly 2.5.

Interpreting these simple ratios as proxies for price impact suggests that daily price impact has declined substantially over time, whereas quarterly price impact has remained largely unchanged. Moreover, the gap between short- and long-term price impact has steadily narrowed and is now relatively small. Put differently, short-term price impact has converged toward long-term price impact.

Figure 6: **Long- versus Short-Term Impact: Qualitative Evidence**
The top two figures plot volatility and (net) volume across stocks at the daily level (Panel (a)) and quarterly level (Panel (b)). The solid lines indicate rolling 10 year averages. The bottom two figures plots the the ratio of return volatility to (net) volume across stocks. We plot rolling 10-year averages.

(a) Daily (b) Quarterly



There is considerable nuance to this argument, as developed in van der Beck et al. (2025). There, we show that the ratio of return volatility to volume provides a *bound* on price impact, conditional on investor disagreement. Intuitively, a large price move with little volume does not necessarily indicate illiquidity—it may simply reflect broad agreement among investors, generating large price moves with little trading activity. The stability of quarterly return volatility and net volume therefore does not unambiguously imply that price impact has remained unchanged. In principle, declining impact could be consistent with these moments if investor agreement has increased over time.[14] Understanding the time-series evolution of investor agreement – for example using analyst beliefs – is an important direction for future research, but goes beyond this simple qualitative motivation.

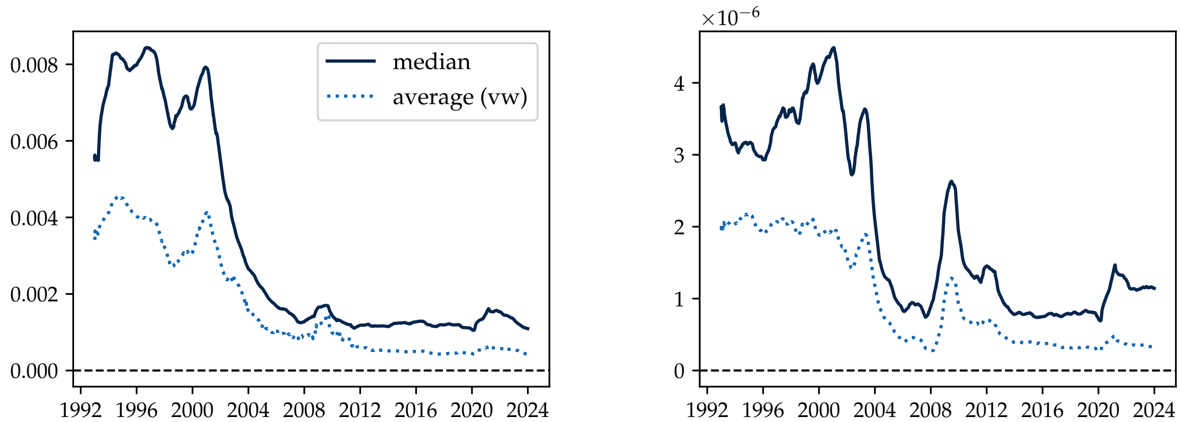
[14]The intuition is simple: Under a declining price impact we should see that the flat net volume generates systematically lower return volatility over time. But return volatility has not declined. Therefore, either price impact has remained unchanged, or investor agreement has increased over time, meaning a larger share of total demand variability is now common (and thus hidden from net volume).

3.2 High-Frequency Liquidity Has Improved

Consistent with the qualitative argument above, we show that the rise in short-horizon trading volume has indeed coincided with considerable improvements in high-frequency liquidity, echoing prior findings (Chordia et al., 2008; Hendershott and Riordan, 2013; Menkveld, 2013; Brogaard et al., 2014b). We present our results in Figure 7. We use two standard high-frequency measures of liquidity: effective spreads and five-minute price impact estimated from signed order imbalance. Effective spreads are computed as $\ln P_k - \ln M_k$ where M_k is the midpoint of the best quote available immediately preceding the trade. Price impact is computed following Hasbrouck (2009) via stock-day level regressions of five-minute midquote returns onto the signed square root dollar order imbalance. Each panel plots rolling 252-day averages. For each trading day, we aggregate these stock-level measures across equities and plot rolling averages over time.[15] Both average effective spreads and five-minute price impact decline sharply between 1992 (the start of TAQ data) and 2024, indicating substantial improvements in high-frequency liquidity over this period.

Figure 7: **High-Frequency Liquidity Over Time**
The figure plots two widely used measures of liquidity: effective spreads and price impact from 1992 to 2024. Panel (a) and (b) plot the median and (value-weighted) average effective spread and price impact across stocks. Effective spreads are computed as $\ln P_k - \ln M_k$ where M_k is the midpoint of the best quote available immediately preceding the trade. Price impact is computed following Hasbrouck (2009) via stock-day level regressions of five-minute midquote returns onto the signed square root dollar order imbalance. Each panel plots rolling 252-day averages.

(a) Effective Spreads (%) (b) 5-Minute Price Impact (λ)



[15]The precise aggregation within a given stock-day—whether equal-weighted, share-weighted, or dollar-weighted—does not affect the results.

3.3 Long-Term Price Impact Has Not Changed

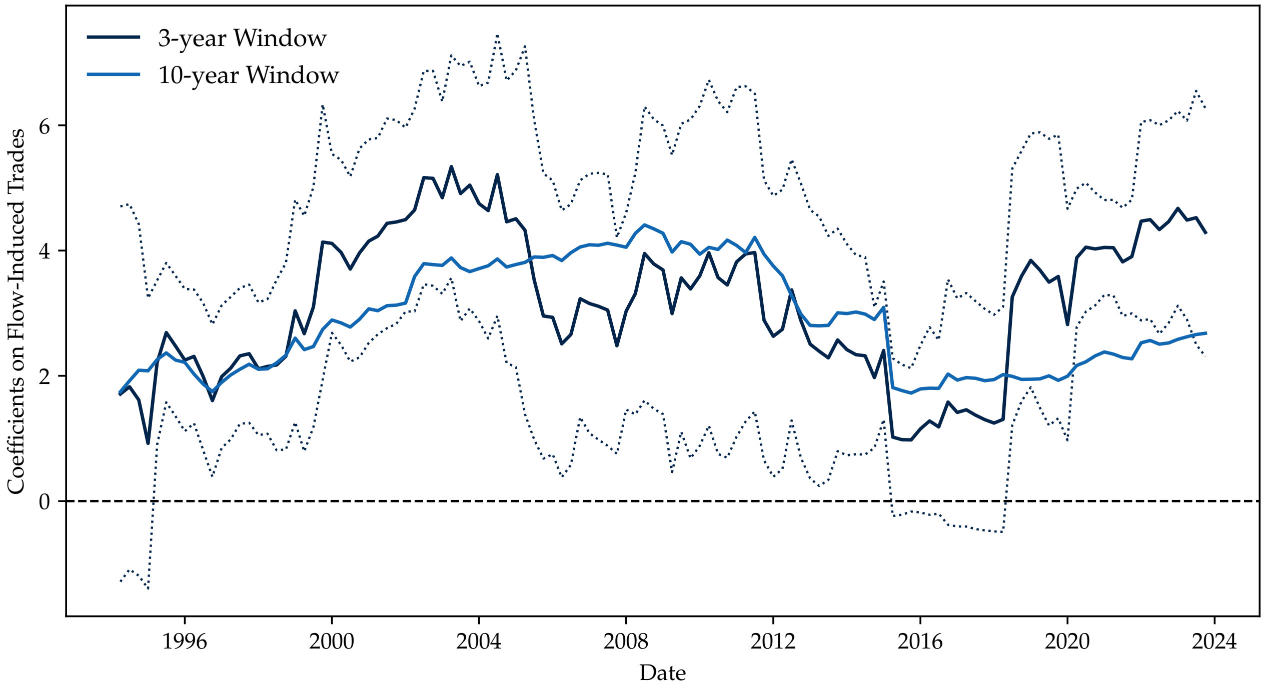
While high-frequency liquidity has evidently improved, our key question is whether long-horizon liquidity has improved as well. The stability of volatility and net volume suggests that it has not. We now test this hypothesis directly using two plausibly exogenous sources of demand shocks widely employed in the literature: mutual fund flow-induced trades (Lou, 2012; van der Beck, 2022) and dividend-induced trades (Schmickler, 2020). For the sake of brevity, we present results using flow-induced trades here and relegate results using dividend-induced trades to Appendix B.2. The results are consistent across both sets of shocks.

Flow-induced trading (FIT) by mutual funds is a widely used source of plausibly exogenous demand shifts in the literature. It is based on the following idea: if mutual fund flows are largely uninformed (Frazzini and Lamont, 2008), then the mechanical buying and selling generated by these flows provides plausibly exogenous cross-sectional variation in stock-level demand. Our construction of quarterly flow-induced trades by mutual funds follows Lou (2012). We regress quarterly returns on flow-induced trades $\text{FIT}_t(n)$ using rolling panel regressions:

$$r_t(n) = \alpha_t + \beta_t \text{FIT}_t(n) + \text{Controls} + \epsilon_t(n), \tag{3}$$

where $\text{FIT}_t(n)$ are stock-level mutual fund flow-induced trades over a quarter expressed as a fraction of shares outstanding. Figure 8 plots the rolling average of β_t from the 1980s to 2023. The average price impact of flow-induced trades has remained essentially constant since the 1980s, with no evidence of a secular decline. This stability implies that the market's capacity to absorb long-term demand shocks has not materially changed. To the extent that fund flows are correlated with the funds' portfolio tilts, flow-induced trades may contain fundamental information and may therefore be correlated with the demand shifts of other investors, which would bias the resulting price-impact estimates. We therefore construct flow shocks by orthogonalizing flows with respect to fund-level characteristics, following van der Beck (2022). Furthermore, previously anticipated flows should not impact prices, akin to announced index inclusions that affect prices at the announcement date rather than on the day the stock is actually included (Greenwood and Sammon, 2025). We therefore construct surprise flows following Chaudhary et al. (2023) and Schmickler (2020). Further details are provided in Appendix A.1. Importantly, the impact estimates remain highly robust and do not depend on orthogonalizing flows with respect to fund characteristics or on constructing flow surprises. Appendix Figure C.2 plots the rolling coefficient on flow-shock induced trades over time and yields the same stable price impact.

Figure 8: **Relationship between Returns and Flow-induced Trades over Time**
The figure plots the estimated coefficients from 3- and 10-year rolling windows regressions of quarterly returns onto quarterly flow-induced trades. The estimated regression coefficients are reported for the period between 1994:Q1 and 2023:Q4.



In Appendix Table C.3, we formally test for the presence of a time trend in price impact and cannot reject the null hypothesis that impact has remained unchanged since the 1980s. Specifically, we interact $\text{FIT}_t(n)$ with either a linear time trend t or decade dummies and find no statistically significant differences in impact over time. In Appendix B.2, we show that the same result obtains using our alternative instrument—dividend-induced trades—that generates plausibly more exogenous shifts in demand.

3.4 Long-Term Price Impact under Alternative Impact Models

Our baseline specification scales flow-induced trades by shares outstanding. We view this as a natural benchmark corresponding to buying 1% of the outstanding supply. Under this baseline, long-term price impact has remained largely unchanged over the past four decades. Notably, because gross trading volume has increased substantially over time, this implies that long-term impact – when measured as a fraction of volume (as is common in industry practice) – has in fact *increased*. Intuitively, buying

1% of shares outstanding today represents a much smaller fraction of daily volume than it did in 1980. Scaling demand shifts by shares outstanding is therefore our preferred baseline, because the level of the alternative denominator (gross volume) has significant time trends making the regression coefficients more difficult to interpret. Nevertheless, *increasing* price impact over time when trades are scaled by daily volume is perhaps even more striking and further reinforces our central claim: the apparent rise in long-term liquidity largely reflects the growth of high-frequency round-trip trading rather than a genuine increase in the market's capacity to absorb fundamental demand shifts. To align our estimates more closely with standard industry measures of price impact, we conduct three alternative tests:

$$r_t(n) = \alpha_t + \beta_t f(\text{FIT}_t(n)) + \text{Controls} + \epsilon_t(n), \tag{4}$$

where $f(\text{FIT}_t(n))$ denotes different transformations of flow-induced trades. We first choose $f(\text{FIT}_t(n)) = \frac{\text{FIT}_t(n)}{\text{Gross Vol.}_t(n)}$ to examine whether demand shifts measured as a fraction of gross trading volume have indeed become more impactful over time. Second, we allow for concave price impact by using $f(\text{FIT}_t(n)) = \text{sign}(\text{FIT}_t(n))\sqrt{\frac{|\text{FIT}_t(n)|}{\text{Gross Vol.}_t(n)}}$, consistent with the well-documented square-root specification in the market microstructure literature (Bouchaud et al., 2018; Tóth et al., 2011) and more recently, the demand-based asset pricing literature (Chaudhry and Li, 2025). Third, we introduce a volatility pre-factor $f(\text{FIT}_t(n)) = \sigma_t(n)\text{sign}(\text{FIT}_t(n))\sqrt{\frac{|\text{FIT}_t(n)|}{\text{Gross Vol.}_t(n)}}$ where $\sigma_t(n)$ denotes quarterly return volatility estimated over the previous 5 years. This specification mirrors standard industry measures of market impact and is consistent with theoretical models in which price impact scales with volatility and trading activity (Kyle and Obizhaeva, 2016).

For simplicity, we divide the sample into two subperiods: an earlier period (1980-2005) and a later period (2005-2023). We then compare the estimated coefficients across the two subsamples. Appendix Table C.5 reports the results. Under our baseline specification, which scales flow-induced trades by shares outstanding, the estimated coefficient is virtually identical across the two periods. Second, consistent with the fact that a 1% trade relative to shares outstanding represents a smaller share of daily volume today, the volume-scaled specification shows a substantial increase in impact. For the square-root specifications, the estimated coefficients also increase in the later period, although the magnitude of the increase is more moderate. Importantly, none of the specifications indicate any decline in long-term price impact. We also conduct a horserace across the alternative specifications. The version scaling trades by shares outstanding statistically dominates those that scale by gross volume. This finding further supports our interpretation that the growth in high-frequency round-trip trading has contributed little to the market's ability to absorb long-term shifts in fundamental demand.[16]

3.5 Mean Reversion Across Horizons

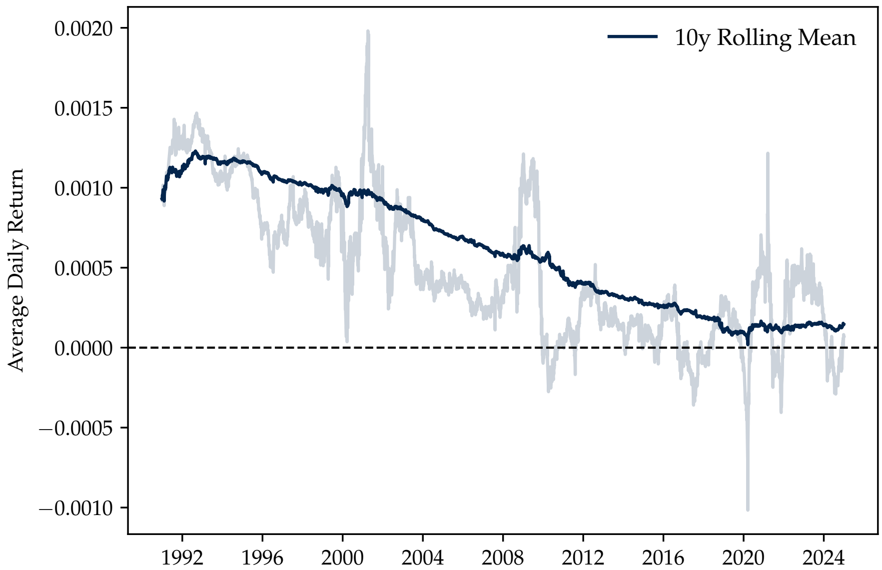
Another widely used measure to assess market liquidity is mean reversion in stock returns. In an illiquid market where short-horizon liquidity providers have limited capacity, non-fundamental demand shifts often cause larger initial price impacts that subsequently mean-revert, leading to predictable patterns in abnormal returns; in a liquid market where short-horizon liquidity providers have ample capacity, such mean reversion should be less pronounced.

If long-term price impact has remained unchanged (as we argue above), while short-term impact has declined (as reflected in narrower spreads), this pattern can only arise if return reversals have changed over time. In the absence of reversal, long-term price impact would equal the cumulative short-term impact and would therefore unambiguously decrease when short-term impact declines.

A large gap between short- and long-term price impact, as likely prevailed before the rise of high-frequency intermediation, implies strong short-term return reversal. As short- and long-term impacts converge, the scope for short-term reversal declines. Accordingly, constant long-term impact combined with declining short-term impact implies weaker reversion to the long-run equilibrium. This yields a clear prediction: The returns to short-term reversal strategies should have declined over time. The returns to short-term reversal strategies can be interpreted as a proxy for compensation for liquidity provision (Nagel, 2012). Following that paper, we construct the daily returns to a high-frequency reversal strategy that weights stocks inversely based on their prior five days' returns. Figure 9 plots the moving average of daily returns from this reversal strategy over time.

[16] In Section 4, we show that quarterly net volume (as opposed to gross volume) does contain incremental information about long-term price impact beyond shares outstanding.

Figure 9: **Decline of High-Frequency Reversal**
The figure plots rolling average returns to high-frequency reversal strategies following Nagel (2012). Reversal strategy returns are the average of returns from five reversal strategies with weights proportional to (negated) of market-adjusted returns on days $t-1, ..., t-5$. Weights are scaled to add up to \$1 for the short- and long leg respectively. The transparent and dark blue line plot 1-year and 10-year moving averages of daily returns respectively.



The figure shows that the returns to liquidity provision have systematically declined over time. Appendix Figure C.4 confirms this using daily Fama-MacBeth regressions of returns on their cumulative three-day lags, controlling for market beta and size. The FMB coefficient on the (negated) past 3-day return is statistically significant and has declined systematically over time.

The decline of the returns to short-term reversal is in line with the improved high-frequency liquidity shown. While this indicates that the gap between short- and long-term impact has narrowed over time, the evidence alone cannot rule out changes in long-term price impact itself. Our central contribution is not to document the decline in high-frequency impact – which is well established – but to show that long-term impact has remained largely unchanged. If this interpretation is correct, we should observe not only a weakening of short-term reversal, but stability in reversal patterns at longer horizons.

We therefore assess short- and long-term reversal patterns systematically across horizons. Specifically, we study mean reversion using variance ratios, which are commonly employed in the literature as indicators of market liquidity and efficiency (Lo and MacKinlay, 1988; Poterba and Summers, 1987; Chordia et al., 2011). Variance ratios provide a more powerful and direct test of serial dependence than simple strategy returns, as they exploit the full time series of returns and aggregate information about autocorrelation across horizons in a unified econometric framework.

We define the variance ratio at frequency k for the stock n as

$$VR_k(n) = \frac{\mathrm{Var}(r^a_{k,t}(n))}{k \cdot \mathrm{Var}(r^a_t(n))}. \tag{5}$$

We consider five frequency pairs spanning short and long horizons: daily-to-monthly ($k = 21$), weekly-to-monthly ($k = 4$), daily-to-yearly ($k = 252$), monthly-to-yearly ($k = 12$), and quarterly-to-yearly ($k = 4$). $r^a_t(n)$ denotes the one-period (base frequency) abnormal return, defined below, and $r^a_{k,t}(n) = \sum_{j=0}^{k-1} r^a_{t-j}(n)$ is the k-period abnormal return.[17] When abnormal returns follow random walks, $VR_k(n) = 1$. A variance ratio below one indicates negative autocorrelation, or mean reversion, in returns.

To construct abnormal returns, we run a cross-sectional regression of stock returns on lagged characteristics associated with the most common pricing factors: market beta, size, and book-to-market. We do not take a stance on whether these pricing factors reflect risk compensation or mispricing. Instead, we take the perspective of Kozak et al. (2018) that any strong comovement in asset prices, even if driven by sentiment, represents systematic risk to arbitrageurs and requires risk compensation. Hence, we focus on the idiosyncratic returns.[18] We also include Fama-French 48 industry fixed effects to further absorb common variation. The regression residuals constitute our abnormal returns.[19]

For each stock-year, we estimate $VR_k(n)$ using the overlapping estimator of Lo and MacKinlay (1988) over rolling 12-year windows. Confidence intervals are computed using a stationary bootstrap that accounts for both cross-sectional clustering by industry and time-series dependence (see Appendix A.2 for details).

Figure 10 plots the cross-sectional average variance ratios from 1990 to 2024. Panel (a) shows short-horizon variance ratios: daily-to-monthly and weekly-to-monthly. Both variance ratios have increased markedly over our sample period, indicating a significant reduction in within-month mean reversion at daily and weekly frequencies. These patterns mirror the large increase in gross trading volume and echo the findings in Chordia et al. (2011) that at high frequencies the increase in trading activity is associated with improved market liquidity.

[17] We use simple returns rather than log returns because abnormal returns after residualization can be smaller than -1. Using log returns by dropping these observations does not affect our results.

[18] In the main text, we do not residualize against momentum and reversal factors, so the variance ratio trends may partly reflect changes in these return premia. Appendix Figure C.5 shows that the results are virtually unchanged when we include them.

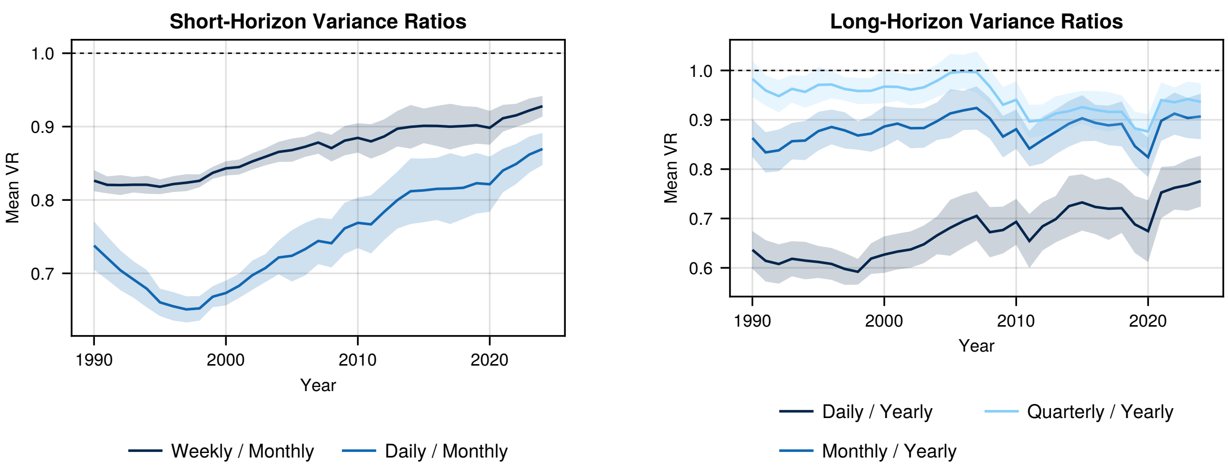
[19] Our results also hold when we residualize returns in the time series against the factors directly. We favor the cross-sectional approach as it only uses information available at the time of the return.

Panel (b) presents variance ratios at longer horizons. In contrast to the steady increase in the daily-to-yearly variance ratio, the monthly-to-yearly and quarterly-to-yearly ratios are consistently below one and remain largely stable. At the monthly frequency, the variance ratio hovers around 0.9, indicating that about 10% of the variance in monthly returns is reversed over the subsequent months within a year. The quarter-to-yearly variance ratio hovers around 0.95, and if anything, has slightly declined.

Taken together, mean-reversion patterns have declined at daily and weekly frequencies, indicating improved liquidity, while at monthly and quarterly frequencies mean reversion has remained stable over the last four decades. This finding is consistent with the pattern that at high frequencies the price impact has declined significantly, while over longer horizons the price impact has remained stable.

Figure 10: **Variance Ratios Over Time At Different Frequencies**
The figure plots average variance ratios across stocks at multiple frequency pairs, estimated using rolling 12-year windows with the Lo and MacKinlay (1988) overlapping estimator. Abnormal returns are residualized against Fama-French 3 characteristics (beta, size, book-to-market) and 48 industry fixed effects. Panel (a) shows short-horizon variance ratios (daily-to-monthly and weekly-to-monthly). Panel (b) shows long-horizon variance ratios (daily-to-yearly, monthly-to-yearly, and quarterly-to-yearly). The sample period is 1980–2024. Shaded regions indicate 95% confidence intervals computed using stationary bootstrap clustered by industry.

(a) Short-Horizon Variance Ratios (b) Long-Horizon Variance Ratios



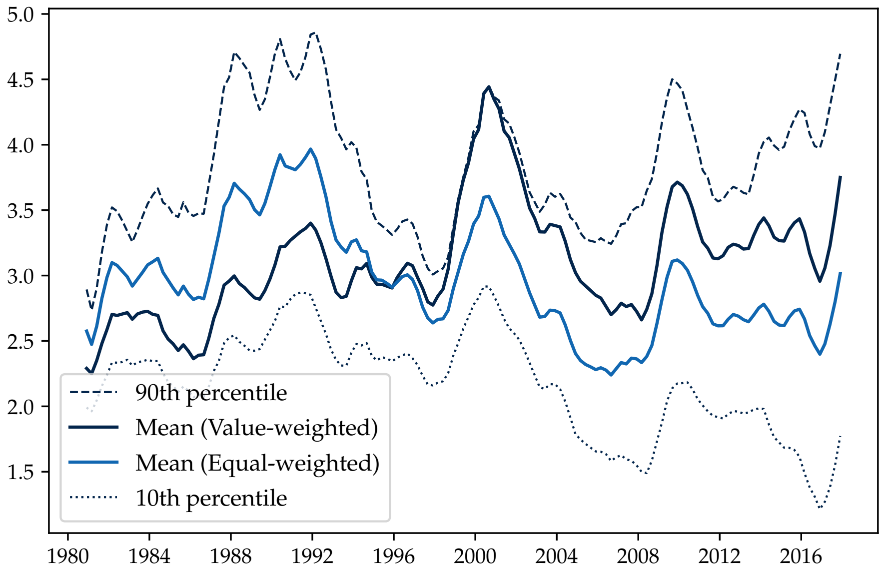
3.6 Structural Evidence

Beyond the reduced-form evidence based on plausibly exogenous demand shocks, we also provide structural evidence following Koijen and Yogo (2019). To our knowledge, this is the only structural framework that delivers estimates of *long-term* price impact. Their model estimates institution-specific demand elasticities from the cross-section of portfolio holdings. Combined with observed portfolio weights, these elasticities pin down the equilibrium price impact of persistent demand shifts. Koijen and Yogo (2019) refer to the resulting object as the aggregate coliquidity matrix, given by

$$\sum_i \frac{\partial \mathbf{p}_t}{\partial \ln \epsilon_{i,t}} = \left(\mathbf{I} - \sum_i \beta_{0,i,t} A_{i,t} \mathbf{H}_t^{-1} \mathbf{G}_{i,t} \right)^{-1} \sum_i A_{i,t} \mathbf{H}_t^{-1} \mathbf{G}_{i,t} \tag{6}$$

where $\epsilon_{i,t}(n)$ is a vector of investor i's latent demand shifts, $\beta_{0,i,t}$ is the demand coefficient for market equity, $A_{i,t}$ are assets under management, and $\mathbf{H}_t^{-1}\mathbf{G}_{i,t}$ is a matrix capturing the ownership distribution across stocks.[20] The diagonal elements of the aggregate coliquidity matrix measure the long-term price impact of persistent demand shifts. Figure 11 plots the cross-sectional distribution of long-term impact over time.

Figure 11: **Long-Term Impact: Structural Evidence**
The figure plots the diagonal elements of the aggregate coliquidity matrix from Koijen and Yogo (2019). We report the top and bottom deciles, as well as market-cap-weighted and equal-weighted averages across all stocks. The series are shown as rolling annual averages of the quarterly impact estimates.



Note that the precise horizon of the impact is not explicit, as the elasticities are estimated from the cross-section of portfolio holdings. However, van der Beck (2022) show that demand coefficients identified from holdings in levels correspond to long-run elasticities, reflecting slow-moving portfolio adjustments over at least one year. Figure 11 shows that, on average, long-term price impact has not materially declined over time. If anything, the market-cap-weighted average impact has slightly increased over time. This pattern is consistent with Haddad et al. (2021), who document that the rise

[20]Formally, $\mathbf{H}_t^{-1}\mathbf{G}_{i,t} = \left(\sum_i \text{diag}(\mathbf{w}_{i,t})A_{i,t}\right)^{-1} \text{diag}(\mathbf{w}_{i,t} - \mathbf{w}_{i,t}\mathbf{w}_{i,t}')$ where $\mathbf{w}_{i,t}$ is a vector of portfolio weights.

of passive investing has not been fully offset by greater elasticity among active investors, leading to an increase in the equilibrium price impact over time.

4 Net Volume vs Gross Volume: Cross-Sectional Evidence

We now provide indirect evidence that long-term impact has remained unchanged from the cross-section of stocks. To this end, we revisit some of the most widely used applications of trading volume in the empirical asset pricing literature and test to what extent net volume subsumes or adds value to the existing specification. This exercise provides an indirect test of whether long-term liquidity has remained constant. If net volume serves as a better proxy for long-term liquidity than gross volume in a given cross-sectional application, then the fact that net volume has remained flat over time would suggest that long-term liquidity has likewise remained unchanged. In contrast, if gross volume outperforms net volume, this may be interpreted as evidence that liquidity has indeed improved.

Trading volume has been used along two broad directions. First it has been used for measuring price impact (or liquidity more generally) in the cross-section of stocks. Second, it has been used as a variable for return prediction, either because illiquidity should be compensated with higher expected returns (Amihud, 2002) or because signed volume proxies for a sentiment shock (Campbell et al., 1993). We present three sets of results: cross-sectional variation in long-term price impact, high-frequency liquidity, and liquidity-related return predictability.

4.1 Long-Term Price Impact

If net volume captures long-term liquidity, securities with persistently lower net volume should exhibit larger price responses to demand shocks of the same relative magnitude. We show that net volume explains long-term price impact in the cross section of stocks and subsumes any explanatory power of gross volume.

Trading volume is a widely used measure of supply when estimating long-term price impact of demand shifts. For example, Coval and Stafford (2007), Edmans et al. (2012), Dessaint et al. (2019) divide mutual fund trades by volume in their price impact regressions. Instead Frazzini and Lamont (2008), Lou (2012), and Pavlova and Sikorskaya (2022) scale by shares outstanding (or market equity when the demand shock is expressed in dollars). We test whether interacting our two demand shocks, flow-induced trades and dividend-induced trades, with net volume versus gross volume explains long-term price impact in the cross-section. To this end, we interact flow-induced trades with lagged net and gross volume to assess whether cross-sectional differences in net and gross volume explain variation in price impact. We use lagged volume to avoid a mechanical contemporaneous correlation, since flow-induced trades mechanically increase both gross and net volume.

$$r_t(n) = \alpha_t + \beta_1 \frac{\text{Demand Shift}_t(n)}{\text{Shrout}_{t-1}(n)} + \beta_2 \frac{\text{Demand Shift}_t(n)}{\text{Gross Vol}_{t-1}(n)} + \beta_3 \frac{\text{Demand Shift}_t(n)}{\text{Net Vol}_{t-1}(n)} + \epsilon_t(n) \tag{7}$$

where Demand $\text{Shift}_t(n)$ is either flow-induced trades (FIT) or dividend-induced trades (DIT), both expressed as numbers of shares purchased. Table 2 reports the results. Panel (a) reports results for FIT. The interaction of demand shifts with net volume is positive and highly significant, whereas the interaction with gross volume is small and statistically insignificant. The same pattern obtains for DIT in Panel (b). Taken together, these results indicate that long-term price impact is systematically related to net trading activity – i.e., the amount of portfolio turnover – rather than to gross trading volume, which largely reflects short-horizon round-trip trades. Markets absorb flow-induced demand shocks more easily in stocks with higher net volume, but gross volume does not provide comparable information about long-term liquidity.

Table 2: **Impact of Flow-Induced Trades**

This Table reports results from regressing quarterly returns onto flow-induced trades (FIT) in Panel (a) and dividend-induced trades (DIT) in Panel (b). The raw demand measures are scaled by quarterly shares outstanding. *Gross FIT* and *Gross DIT* denote the ratio relative to gross volume. Conversely, *Net FIT* and *Net DIT* denote the ratios relative to net volume. The sample period is from 1980:Q1 to 2023:Q4. The reported standard errors in parentheses are clustered by date.

(a) Flow-Induced Trades

	$LNret_Q$				
	(1)	(2)	(3)	(4)	(5)
FIT	3.006*** (0.498)			1.792** (0.598)	
gross FIT		0.861*** (0.109)		0.075 (0.158)	0.158 (0.151)
net FIT			0.542*** (0.062)	0.269** (0.096)	0.458*** (0.084)
Date	x	x	x	x	x
Observations	423911	410650	423911	410650	410650
R^2	0.172	0.174	0.172	0.174	0.174
R^2 Within	0.002	0.002	0.002	0.003	0.002

Significance levels: $*$ p $<$ 0.05, $**$ p $<$ 0.01, $***$ p $<$ 0.001. Format of coefficient cell: Coefficient (Std. Error)

(b) Dividend-Induced Trades

	$LNret_Q$				
	(1)	(2)	(3)	(4)	(5)
DIT	11.421*** (1.433)			5.860*** (1.255)	
gross DIT		1.543*** (0.222)		0.336 (0.195)	0.619** (0.190)
net DIT			1.592*** (0.200)	1.043*** (0.170)	1.253*** (0.175)
Date	x	x	x	x	x
Observations	796058	758301	796001	758253	758253
R^2	0.164	0.163	0.165	0.165	0.164
R^2 Within	0.003	0.003	0.004	0.005	0.004

Significance levels: $*$ p $<$ 0.05, $**$ p $<$ 0.01, $***$ p $<$ 0.001. Format of coefficient cell: Coefficient (Std. Error)

4.2 High-Frequency Liquidity

Does net volume also help explain high-frequency liquidity, despite being observed only at quarterly frequency? Trading volume may affect high frequency liquidity via adverse selection risk (Kyle, 1985; Glosten and Harris, 1988) and inventory risk (Stoll, 1978). Liquidity provision hinges on expectations about future offsetting order flow: liquidity providers are more willing to absorb temporary demand shocks when they anticipate a higher likelihood of subsequent offsetting trades, leading to narrower spreads and greater depth (Demsetz, 1968). This likelihood should perhaps increase with net volume. If net volume reflects the ultimate source of high-frequency gross volume, it may therefore help explain cross-sectional variation in high-frequency price impact. To investigate this, we estimate the following regression:

$$\text{HFT-Liquidity}_t(n) = \alpha_t + \beta_1 \text{Net Vol}_t(n) + \beta_2 \text{Gross Vol}_t(n) + \text{Controls} + \epsilon_t(n), \tag{8}$$

where $\text{HFT-Liquidity}_t(n)$ denotes either log effective spreads or five-minute price impact from signed order imbalance. To treat gross volume fairly – given its availability at a high frequency – we include both contemporaneous daily gross volume and lagged quarterly gross volume as controls. Net volume is only available at the quarterly frequency. More recently, Bogousslavsky and Collin-Dufresne (2023) show that order-imbalance volatility ($HFOIV$) is an important driver of liquidity and can explain the often positive time-series relationship between spreads and volume, which runs counter most theoretical models. We therefore also include $HFOIV$ in our regressions. All volume measures are expressed as fractions of shares outstanding. Table 3 reports the results.

Table 3: **Net Volume and High-Frequency Liquidity**
This table reports panel regressions of high-frequency liquidity measures on net volume, controlling for gross trading volume, high frequency order imbalance volatility, firm size and return volatility. The dependent variable is either the log effective spread (*spread*; columns (1)-(4)) or five-minute price impact from signed order imbalance (*lambda*; columns (5)-(8)). Gross volume is measured both at the daily frequency and at the quarterly frequency, while net volume is available only quarterly. All volume measures are scaled by shares outstanding. High frequency order imbalance volatility (HFOIV) is from Bogousslavsky and Collin-Dufresne (2023). All specifications include time and/or stock fixed effects as indicated. Double-clustered standard errors by stock and day are reported in parentheses.

	spread				lambda			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log Market Cap	-0.507***	-0.598***	-0.458***	-0.573***	-0.182***	-0.354***	-0.186***	-0.338***
	(0.011)	(0.017)	(0.010)	(0.016)	(0.005)	(0.009)	(0.005)	(0.009)
Volatility	0.079***	0.057***	0.124***	0.076***	0.124***	0.076***	0.140***	0.080***
	(0.004)	(0.003)	(0.005)	(0.003)	(0.002)	(0.002)	(0.003)	(0.002)
Net Volume	-0.204***	-0.064***	-0.150***	-0.052***	-0.037***	-0.018***	-0.018***	-0.014***
	(0.007)	(0.003)	(0.006)	(0.003)	(0.003)	(0.002)	(0.002)	(0.001)
Daily Gross Volume			-0.064***	-0.025***			0.008***	0.020***
			(0.003)	(0.002)			(0.001)	(0.001)
Quarterly Gross Volume			-0.109***	-0.089***			-0.022***	-0.024***
			(0.007)	(0.005)			(0.002)	(0.002)
HFOIV			0.102***	0.072***			-0.063***	-0.061***
			(0.003)	(0.002)			(0.001)	(0.001)
Day	x	-	x	x	x	-	x	x
Stock	-	x	-	x	-	x	-	x
Observations	8024758	8024758	8024758	8024758	8024758	8024758	8024758	8024758
R^2	0.322	0.492	0.336	0.514	0.073	0.110	0.077	0.122
R^2 Within	0.312	0.068	0.327	0.076	0.062	0.019	0.066	0.018

Significance levels: $*$ p $<$ 0.05, $**$ p $<$ 0.01, $***$ p $<$ 0.001. Format of coefficient cell: Coefficient (Std. Error)

Table 3 highlights that net volume is strongly related to high-frequency liquidity, even after controlling for gross trading activity and high frequency order imbalance volatility. Across specifications, higher net volume is associated with lower effective spreads and lower short-horizon price impact. The effect of net volume remains statistically significant when controlling simultaneously for contemporaneous daily gross volume and lagged quarterly gross volume, indicating that net volume contains information about high-frequency liquidity beyond that captured by overall trading activity. In contrast, gross volume exhibits an economically weaker relationship with liquidity. The results are robust to different combinations of stock and time fixed effects. Appendix Table C.4 shows that this pattern holds statistically across stocks of all sizes. We split the sample into size quintiles and find that net volume predicts significantly lower spreads in every quintile. Economically, however, the relationship weakens with firm size. For the largest quintile of stocks, net volume remains a significant predictor of lower spreads, whereas gross volume is not related to spreads in the cross section.

4.3 Return Predictability

Trading volume is a widely used predictor of returns, either directly or in volume-based liquidity proxies such as Amihud (2002) or Brennan et al. (2013). The predictive power has been attributed either to compensation for illiquidity or to sentiment-driven mispricing (Baker and Stein, 2004). We do not take a stance on the underlying mechanism, we rather examine whether net volume provides incremental information for return predictability, particularly at lower frequencies such as monthly or quarterly horizons. First, as discussed above, net volume may more accurately reflect actual liquidity, understood as the market's ability to permanently absorb and offset order flow. Second, net volume may better capture sentiment-driven demand shocks by filtering out high-frequency noise due to financial intermediation.

We start by reporting portfolio sorts based on either gross or net volume. Each month, we sort stocks into quintiles using lagged gross and net volume. All volume measures are scaled by shares outstanding and therefore correspond to turnover. Panel (a) of Table 4 reports monthly four-factor alphas for the quintile portfolios and the high-minus-low (H-L) portfolios. Sorting on gross volume produces neither an apparent return pattern across portfolios nor a significant H-L return spread. In contrast, stocks with higher net volume earn lower subsequent returns, with alphas declining across net-volume quintiles. Moreover, the H-L portfolio has a monthly four-factor alpha of -33 basis points, significant at the 1% level. Appendix Table C.6 further reports double sorts on gross and net volume. Within each net-volume quintile, the return spread between high and low gross volume stocks is insignificant. In contrast, sorting first on gross volume and then on net volume results in return spreads that are negative and highly statistically significant. These findings are further confirmed in Fama-MacBeth regressions of four-factor adjusted returns onto both gross and net volume, controlling for size and high frequency order imbalance volatility (Bogousslavsky and Collin-Dufresne, 2023). Panel (b) of Table 4 shows that across different sets of controls, net volume significantly predicts negative returns.

Table 4: **Gross Volume versus Net Volume: Return Predictability**
Panel (a) sorts stocks based on gross and net volume (using NYSE breakpoints). Both measures are scaled by shares outstanding and therefore capture turnover. We report four-factor equal-weighted alphas (in percent). Panel (b) reports monthly Fama-MacBeth regression results of future four-factor (MKT, SMB, HML, and UMD) adjusted returns onto gross volume, net volume, market equity, and high frequency order imbalance volatility (HFOIV) from Bogousslavsky and Collin-Dufresne (2023). Monthly HFOIV is an exponentially-weighted moving average of prior high-frequency (i.e., daily) order imbalance volatility with a half-life of one day. The reported t-statistics are Newey-West robust with 6 lags. We exclude micro-caps, i.e., firms that are smaller in terms of market equity than the 10th-percentile of NYSE firms. The sample consists of NYSE, Amex, and NASDAQ common stocks over 1980–2023. t-statistics are reported in parentheses and computed using Newey-West standard errors with six lags. *, **, and *** denote significance at the 10%, 5%, and 1% level.

(a) Portfolio Sorts (α^{EW}_{FF4})

low gross Vol.	2	3	4	high gross Vol.	H - L
0.196	0.215	0.255	0.189	0.246	0.049
low net Vol.	2	3	4	high net Vol.	H - L
0.424	0.186	0.196	0.144	0.093	-0.331***

(b) FMB Regressions

	Dependent Variable: Four-Factor-adjusted Returns								
gross Vol.	-0.378		-0.149		0.144	0.248		-0.830	
	(-0.64)		(-0.25)		(0.25)	(0.42)		(-1.45)	
net Vol.		-0.925***		-0.688**	-0.961***	-0.778***			-0.459
		(-3.27)		(-2.45)	(-3.75)	(-3.25)			(-1.42)
ln(Mcap)			-0.181***	-0.163***		-0.167***		0.012	0.004
			(-4.95)	(-5.00)		(-4.75)		(0.33)	(0.11)
HFOIV							35.790	59.045**	38.978
							(1.16)	(2.47)	(1.37)
Adj. R^2	0.006	0.002	0.009	0.005	0.008	0.011	0.001	0.009	0.005
Avg. Obs	1872	1853	1872	1853	1853	1853	1885	1885	1870

Significance levels: $*$ p $<$ 0.1, $**$ p $<$ 0.05, $***$ p $<$ 0.01.

A more widely used liquidity measure for return prediction, rather than raw turnover, is Amihud illiquidity (Amihud, 2002), defined as the daily absolute return divided by volume and averaged over the previous month. We examine whether replacing gross volume with net volume provides incremental information. We refer to the two measures as Gross Amihud and Net Amihud, respectively, and describe their construction in Appendix A.2.4. Appendix Table C.7 documents that univariately both measures positively and significantly predict returns in portfolio sorts and Fama-MacBeth regressions. In contrast to Gross Amihud, Net Amihud remains robustly and highly significant across all specifications, including those controlling for size, Gross Amihud, or both.

Overall, these results substantiate our finding that net volume provides incremental information beyond gross volume. In particular, net volume is less distorted by high-frequency round-trip trades, which cannot (directly) contribute to the market's long-term ability to absorb flows. As a result, net volume provides a more reliable measure of long-term liquidity and, consequently, of price impact.

5 Net Volume for the Aggregate Stock Market

Total dollar gross volume in the aggregate stock market is typically computed as the sum of trading volume across all U.S. stocks over a given period (Hong and Stein, 2007). By construction, this measure counts the dollar value of all trades that occur. In the final quarter of our sample, aggregate gross volume reaches nearly \$20 trillion–roughly 50% of total market equity.[21] However, gross volume substantially overstates economically meaningful trading at the market level over a given horizon. It includes investors reallocating across stocks – buying one stock while selling another – which constitutes a cross-sectional round-trip trade rather than a flow into or out of the stock market. It also includes purchases and sales that offset over time, such as short-horizon market timing, generating time-series round-trip trades. Both types of round-trip trading potentially inflate gross volume without corresponding to economically meaningful changes in investors' long-term equity allocations.

5.1 Round-trips over Time versus Across Assets

Round-trip trades can occur over time or across assets. In the cross-section, buying \$1 billion of Apple (AAPL) while simultaneously selling \$1 billion of Alphabet (GOOG) constitutes a round-trip trade: aggregate demand for equities is unchanged, yet trading volume is high. In the time series, buying \$1 billion of Apple and selling the same stock one second later is likewise a round-trip trade, but in the time-series. At the level of the aggregate stock market, both cross-sectional and time-series round-trip trades inflate gross trading volume relative to net trading volume, even though they do not reflect actual portfolio reallocations at the given horizon.

5.2 Measuring Market Level Net Volume

Our goal is to measure net flows into and out of the aggregate stock market, rather than trading activity that merely reshuffles positions across stocks and at a high frequency. A natural first step is to compute stock-level net dollar volume as used in the previous sections and aggregate across stocks,

[21] See Appendix Table C.8 for a display of the 2023 numbers of dollar volumes and turnover.

yielding what we call *cross-sectional net volume.* For the aggregate U.S. stock market, cross-sectional net volume amounts to roughly \$3 trillion in the final quarter of our sample, or about 6% of total market equity. However, cross-sectional net volume still overstates aggregate reallocation because it does not net out offsetting trades across stocks. An investor who buys one stock and sells another contributes positively to cross-sectional net volume, despite having zero net exposure to the stock market as a whole. We therefore define total net volume for the aggregate stock market as

$$\text{Market Net Volume}_t = \frac{0.5 \sum_{i=1}^{I} \left| \sum_{n \in N_i} \Delta Q_{i,t}(n) P_t(n) \right|}{\text{Total Stock Market Equity}_t}, \tag{9}$$

where N_i is the set of stocks held by investor i. Market net volume directly measures investor-level flows into and out of the equity market. In the final quarter of our sample, market net volume is only 2.5% of total market equity – nearly twenty times smaller than gross trading volume.[22] The numerator in (9), $\left|0.5 \sum_{n \in N_i} \Delta Q_{i,t}(n) P_t(n)\right|$, measures investor i's net flow into or out of the aggregate stock market at time t. This term is zero if the investor exclusively engages in cross-sectional round-trip trades. By contrast, cross-sectional net volume uses $0.5 \sum_{i=1}^{I} \sum_{n \in N_i} |\Delta Q_{i,t}(n)| P_t(n)$ in the numerator and therefore does not net out such trades.

5.3 The Evolution of Market Level Net Volume

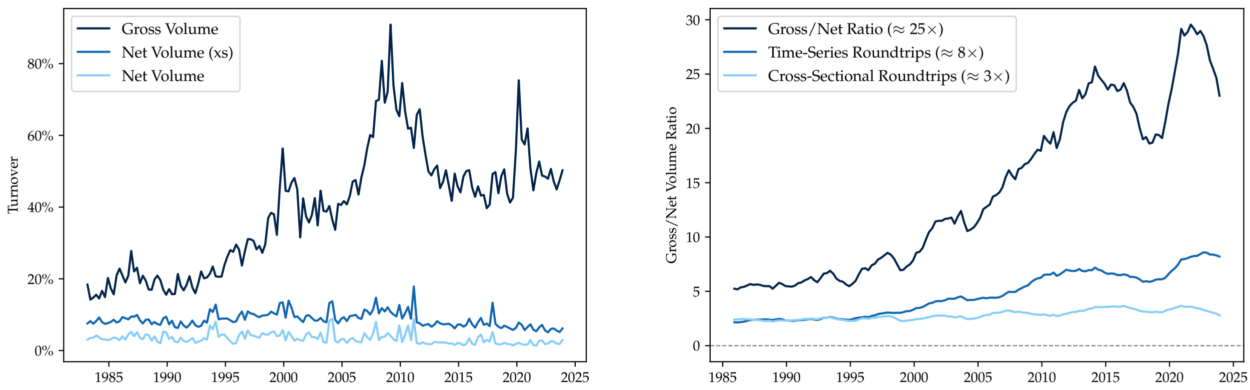
Panel (a) of Figure 12 plots gross market volume, cross-sectional net volume, and market net volume. While both cross-sectional net volume and market net volume remain relatively stable over time, gross trading volume has increased sharply. This divergence implies that the rise in gross volume is not driven by an increase in economically meaningful reallocation. Instead, it reflects a pronounced growth in time-series round-trip trading, while the amount of cross-sectional round-trip trading remains broadly unchanged. Panel (b) of Figure 12 formalizes this intuition by plotting ratios of the different volume measures. The ratio of gross volume to market net volume increases steadily from roughly 5x to 25x over the sample period. We next plot the ratio of gross volume to cross-sectional net volume, which isolates the contribution of time-series round-trip trades. This ratio rises from about 2 to 8, closely mirroring the increase in gross-versus-net volume observed at the stock level. Finally, we plot the ratio of cross-sectional net volume to market net volume, which captures the contribution of cross-sectional round-trip trades. This ratio remains approximately constant at around 3 throughout the sample,

[22] The denominator in (9) is total stock market equity, given by $\sum_n P_t(n) \cdot \text{Shrout}_t(n)$.

indicating that cross-sectional round-trip trading has not materially changed over time.

Figure 12: **Gross versus Net Volume at the Market Level**
Panel (a) plots gross stock market volume against time series net volume (which nets out time-series round-trips) and total net volume (which nets out both time-series and cross-sectional round-trips). All measures are reported as a fraction of market equity. Panel (b) plots the ratio of gross versus total net volume, as well as time-series round-trips (which is the ratio of gross volume/time series net volume) and cross-sectional round-trips (which is the ratio of time series net volume/total net volume).

(a) Gross Volume and Net Volume (%) (b) Gross/Net Volume Ratio



Ultimately, whether trading volume is viewed as a proxy for aggregate sentiment shocks (Baker and Stein, 2004) or for market-wide liquidity (Jones, 2002), *net* trading volume – rather than gross volume – is the economically relevant object at the horizon under investigation. Accordingly, when predicting returns at horizons beyond very high frequency, net volume should dominate gross volume – either because it captures aggregate demand shocks or because it reflects economically meaningful liquidity in terms of portfolio turnover. The next section examines the predictive power of gross versus net trading volume for aggregate stock market returns.

5.4 Net Volume and Aggregate Stock Market Returns

Jones (2002) documents that annual average equity turnover of NYSE stocks negatively predicts market excess returns in a very long sample between 1900 and 2001. This finding is interpreted as liquidity being priced for the aggregate stock market: High average turnover is associated with high liquidity which should predict *low* future stock risk premia.[23] We revisit and run predictive regressions of market excess returns on market level gross and net volume over various return horizons.[24]

[23]Jones (2002) defines annual share turnover as annual total share volume divided by total shares listed on the exchange (i.e., NYSE). We expand on this analysis along two dimensions. First, instead of focusing on NYSE-listed shares only, we consider all stocks that are listed on AMEX, NYSE, or NASDAQ and calculate average quarterly turnover, i.e., *gross volume*.

[24]The excess return on the market is measured as the value-weighted return of all CRSP firms incorporated in the U.S. and listed on the NYSE, AMEX, or NASDAQ that have a CRSP share code of 10 or 11 at the beginning of a given

Table 5 documents that gross volume does not predict future market excess returns at any horizon. This finding is consistent with Jones (2002), who documents that gross trading volume becomes insignificant in the second half of his long sample period.[25] More importantly, however, net volume predicts future returns across all horizons. These findings are also confirmed in multivariate regressions that include both gross and net volume: once orthogonalized to gross volume, net volume becomes an even stronger predictor of future returns across all horizons. The adjusted R^2 rises with the forecast horizon up to 12% for the five-year horizon.

Table 5: **Predictive Regressions: Excess Market Returns**
This Table reports results from quarterly predictive regressions of equity market excess returns on gross and net volume (both defined in terms of turnover, i.e., as a fraction of total stock market equity respectively). Excess market returns are predicted for horizons of 1, 4, 8, 12, 16, and 20 quarters. The sample period is from 1982:Q1 to 2024:Q4. All regressions include a constant term (coefficients not reported). The reported t-statistics are computed from Newey-West robust standard errors.

	1Q	4Q	8Q	12Q	16Q	20Q
Univariate						
Gross Volume	0.002	-0.005	-0.005	-0.005	0.019	0.042
	(0.24)	(-0.17)	(-0.16)	(-0.11)	(0.34)	(0.57)
Adj. R^2	-0.006	-0.005	-0.006	-0.006	-0.004	0.002
N	168	168	164	160	156	152
Net Volume	-0.012*	-0.047**	-0.069**	-0.077*	-0.089*	-0.143**
	(-1.84)	(-2.29)	(-2.04)	(-1.84)	(-1.78)	(-2.43)
Adj. R^2	0.015	0.067	0.074	0.059	0.051	0.087
N	168	168	164	160	156	152
Multivariate						
Gross Volume	0.004	0.004	0.009	0.014	0.045	0.095
	(0.62)	(0.17)	(0.27)	(0.35)	(0.84)	(1.27)
Net Volume	-0.013*	-0.047**	-0.070**	-0.080*	-0.101**	-0.172***
	(-1.97)	(-2.38)	(-2.11)	(-1.95)	(-2.04)	(-3.00)
Adj. R^2	0.012	0.062	0.069	0.055	0.058	0.119
N	168	168	164	160	156	152

An alternative interpretation, following Baker and Stein (2004), views trading volume as a sentiment proxy rather than a liquidity measure.[26] Notably, our empirical analysis does not take a stance on whether net volume predicts returns through sentiment or liquidity. Under the sentiment-based interpretation, the stronger predictive power of net volume relative to gross volume suggests that

month minus the one-month Treasury bill rate.

[25]In particular, Table 4 in Jones (2002) documents that turnover is insignificant (p-value of 0.271) in the subsample between 1951 and 2000.

[26]In their framework, high volume reflects the entry of sentiment-driven traders, which – paired with short-selling frictions – pushes prices above fundamentals, generating subsequent reversals and return predictability. Under this view, turnover predicts returns not because of a liquidity premium, but because it captures contemporaneous non-fundamental demand pressure.

non-fundamental demand shifts are more closely tied to net portfolio reallocations than to cumulative round-trip trading activity. Because gross volume is often amplified by high-frequency intermediation that obscures underlying demand imbalances, net volume may provide a cleaner proxy for sentiment-driven shocks.

6 Conclusion

This paper rethinks the role of trading volume as a measure of market liquidity. We document that while gross trading volume has increased dramatically over the past four decades, net volume – trading associated with persistent portfolio reallocations – has remained largely unchanged. Consistent with this fact, long-term price impact and long-horizon variance ratios show no evidence of a secular improvement in market liquidity. The growth in trading activity therefore rather reflects an expansion of short-horizon round-trip trading, primarily associated with high-frequency intermediation, rather than an increased capacity of markets to absorb persistent demand shocks. We provide empirical evidence that net volume is the relevant measure of liquidity at a given horizon. It subsumes gross volume in explaining long-term price impact, predicts returns more strongly across a wide range of specifications, and remains informative even for high-frequency liquidity measures. Gross volume, by contrast, is increasingly contaminated by transitory trading that improves execution at very short horizons but does not contribute meaningfully to long-term liquidity beyond net volume. Finally, we cannot rule out that high-frequency trading activity, even though it cannot provide long-term liquidity to persistent demand shifts *directly*, may *indirectly* foster liquidity provision in the long run. For example, a long-term liquidity-providing value investor may avoid stocks that are not intermediated by high-frequency traders, as this would imply high trading costs during fire sales. In this sense, high-frequency liquidity may induce the entry of more elastic long-term liquidity providers and thereby lower long-run price impact. Exploring this mechanism is an important avenue for future research.

References

Amihud, Y. (2002). Illiquidity and stock returns: cross-section and time-series effects. *Journal of financial markets 5*(1), 31–56.

Baker, M., J. Coval, and J. C. Stein (2007). Corporate financing decisions when investors take the path of least resistance. *Journal of Financial Economics 84*(2), 266–298.

Baker, M. and J. C. Stein (2004). Market liquidity as a sentiment indicator. *Journal of financial Markets 7*(3), 271–299.

Bogousslavsky, V. and P. Collin-Dufresne (2023). Liquidity, volume, and order imbalance volatility. *The Journal of Finance 78*(4), 2189–2232.

Bouchaud, J.-P., J. Bonart, J. Donier, and M. Gould (2018). *Trades, quotes and prices: financial markets under the microscope.* Cambridge University Press.

Brennan, M., S.-W. Huh, and A. Subrahmanyam (2013). An analysis of the amihud illiquidity premium. *The Review of Asset Pricing Studies 3*(1), 133–176.

Brogaard, J., T. Hendershott, and R. Riordan (2014a). High-Frequency Trading and Price Discovery. *The Review of Financial Studies 27*(8), 2267–2306.

Brogaard, J., T. Hendershott, and R. Riordan (2014b). High-frequency trading and price discovery. *The Review of Financial Studies 27*(8), 2267–2306.

Campbell, J. Y., S. J. Grossman, and J. Wang (1993). Trading volume and serial correlation in stock returns. *The Quarterly Journal of Economics 108*(4), 905–939.

Chaudhary, M., Z. Fu, and J. Li (2023). Corporate bond multipliers: Substitutes matter. *Available at SSRN*.

Chaudhry, A. and J. Li (2025). Endogenous elasticities: Price multipliers are smaller for larger demand shocks.

Chinco, A. and M. Sammon (2024). The passive ownership share is double what you think it is. *Journal of Financial Economics 157*, 103860.

Chordia, T., R. Roll, and A. Subrahmanyam (2005). Evidence on the speed of convergence to market efficiency. *Journal of financial economics 76*(2), 271–292.

Chordia, T., R. Roll, and A. Subrahmanyam (2008). Liquidity and market efficiency. *Journal of financial Economics 87*(2), 249–268.

Chordia, T., R. Roll, and A. Subrahmanyam (2011, August). Recent trends in trading activity and market quality. *Journal of Financial Economics 101*(2), 243–263.

Coval, J. and E. Stafford (2007). Asset fire sales (and purchases) in equity markets. *Journal of Financial Economics 86*(2), 479–512.

Demsetz, H. (1968). The cost of transacting. *The quarterly journal of economics 82*(1), 33–53.

Dessaint, O., T. Foucault, L. Frésard, and A. Matray (2019). Noisy stock prices and corporate investment. *The Review of Financial Studies 32*(7), 2625–2672.

Duffie, D. (2010). Presidential address: Asset price dynamics with slow-moving capital. *The Journal of finance 65*(4), 1237–1267.

Duffie, D. (2018). Financial regulatory reform after the crisis: An assessment. *Management Science 64*(10), 4835–4857.

Edmans, A., I. Goldstein, and W. Jiang (2012). The real effects of financial markets: The impact of prices on takeovers. *The Journal of Finance 67*(3), 933–971.

Frazzini, A., R. Israel, and T. J. Moskowitz (2018). *Trading costs*, Volume 3229719. SSRN.

Frazzini, A. and O. A. Lamont (2008). Dumb money: Mutual fund flows and the cross-section of stock returns. *Journal of financial economics 88*(2), 299–322.

Gabaix, X. and R. S. Koijen (2021). In search of the origins of financial fluctuations: The inelastic markets hypothesis. *Available at SSRN 3686935*.

Gabaix, X., R. S. J. Koijen, F. Mainardi, S. S. Oh, and M. Yogo (2025). Limited Risk Transfer Between Investors: A New Benchmark for Macro-Finance Models.

Gaspar, J.-M., M. Massa, and P. Matos (2005). Shareholder investment horizons and the market for corporate control. *Journal of financial economics 76*(1), 135–165.

Glosten, L. R. and L. E. Harris (1988). Estimating the components of the bid/ask spread. *Journal of financial Economics 21*(1), 123–142.

Greenwood, R. and M. Sammon (2025). The disappearing index effect. *The Journal of Finance 80*(2), 657–698.

Greenwood, R. and D. Scharfstein (2013). The growth of finance. *Journal of Economic perspectives 27*(2), 3–28.

Haddad, V., P. Huebner, and E. Loualiche (2021). How competitive is the stock market? theory, evidence from portfolios, and implications for the rise of passive investing. *Theory, Evidence from Portfolios, and Implications for the Rise of Passive Investing (April 7, 2021)*.

Hartzmark, S. M. and D. H. Solomon (2021). Predictable price pressure. *Available at SSRN 3853096*.

Hasbrouck, J. (2009). Trading costs and returns for us equities: Estimating effective costs from daily data. *The Journal of Finance 64*(3), 1445–1477.

Hendershott, T., C. M. Jones, and A. J. Menkveld (2011). Does algorithmic trading improve liquidity? *The Journal of finance 66*(1), 1–33.

Hendershott, T. and A. J. Menkveld (2014). Price pressures. *Journal of Financial economics 114*(3), 405–423.

Hendershott, T. and R. Riordan (2013). Algorithmic trading and the market for liquidity. *Journal of financial and quantitative analysis 48*(4), 1001–1024.

Hong, H. and J. C. Stein (2007). Disagreement and the stock market. *Journal of Economic perspectives 21*(2), 109–128.

Jones, C. (2002). A century of stock market liquidity and trading costs. *Available at SSRN 313681*.

Koijen, R. S. and M. Yogo (2019). A demand system approach to asset pricing. *Journal of Political Economy 127*(4), 1475–1515.

Kozak, S., S. Nagel, and S. Santosh (2018). Interpreting factor models. *The Journal of Finance 73*(3), 1183–1223.

Kvamvold, J. and S. Lindset (2018). Do dividend flows affect stock returns? *Journal of Financial Research 41*(1), 149–174.

Kyle, A. S. (1985). Continuous Auctions and Insider Trading. *Econometrica 53*(6), 1315–1335.

Kyle, A. S. and A. A. Obizhaeva (2016). Market microstructure invariance: Empirical hypotheses. *Econometrica 84*(4), 1345–1404.

Li, J. and Z. Lin (2022). Price multipliers are larger at more aggregate levels. *Available at SSRN 4038664*.

Lo, A. W. and A. C. MacKinlay (1988). Stock Market Prices do not Follow Random Walks: Evidence from a Simple Specification Test. *The Review of Financial Studies 1*(1), 41–66.

Lou, D. (2012). A flow-based explanation for return predictability. *The Review of Financial Studies 25*(12), 3457–3489.

Menkveld, A. J. (2013). High frequency trading and the new market makers. *Journal of financial Markets 16*(4), 712–740.

Nagel, S. (2012). Evaporating liquidity. *The Review of Financial Studies 25*(7), 2005–2039.

Pavlova, A. and T. Sikorskaya (2022). Benchmarking intensity.

Politis, D. N. and J. P. Romano (1994). The stationary bootstrap. *Journal of the American Statistical Association 89*(428), 1303–1313.

Poterba, J. and L. Summers (1987, August). Mean Reversion in Stock Prices: Evidence and Implications. Technical Report w2343, National Bureau of Economic Research, Cambridge, MA.

Schmickler, S. (2020). Identifying the price impact of fire sales using high-frequency surprise mutual fund flows. *Available at SSRN 3488791*.

Schmickler, S. and P. Tremacoldi-Rossi (2022). Spillover effects of payouts on asset prices and real investment. *Available at SSRN 4287300*.

SEC (2014). Equity market structure literature review Part II: High frequency trading. *Staff of the Division of Trading and Markets*.

Stoll, H. R. (1978). The supply of dealer services in securities markets. *The Journal of Finance 33*(4), 1133–1151.

Tóth, B., Y. Lemperiere, C. Deremble, J. De Lataillade, J. Kockelkoren, and J.-P. Bouchaud (2011). Anomalous price impact and the critical nature of liquidity in financial markets. *Physical Review X 1*(2), 021006.

van der Beck, P. (2022). Short-versus long-run demand elasticities in asset pricing. *Asset Pricing (May 16, 2022). Swiss Finance Institute Research Paper* (22-67).

van der Beck, P., L. Bretscher, and J. Z. Fu (2025). A bound on price impact and disagreement. Technical report, Swiss Finance Institute.

Appendix A Data Construction Details

A.1 Constructing Surprise Flow-Induced Trades

Following Lou (2012), we construct flow-induced trades (FIT) as the product of fund flows and lagged portfolio weights. The measure captures mechanical buying and selling pressure from mutual fund inflows and outflows.

A.1.1 Data Sources, Sample, and Construction

We use Thomson-Reuters S12 quarterly mutual fund holdings data between 1980 and 2024 and merge it with the CRSP Mutual Fund Survivorship-Bias-Free Database for total net assets (TNA) and returns (via MFLINKS tables). We restrict our sample to domestic equity funds (CRSP objective code prefix 'ED') and require that a fund's aggregate holdings value is between 75% and 120% of its reported TNA, ensuring adequate holdings data quality.

Let $F_{i,t}$ denote the quarterly flow (in dollars) into fund i at time t. Quarterly flow-induced trades is then simply given by summing over all hypothetical trades if flows were invested in line with previous portfolio weights $w_{i,t-1}(n)$:

$$FIT_t(n) = \frac{\sum_{i=1}^{I} F_{i,t} w_{i,t-1}(n)}{ME_{t-1}(n)} \tag{A.1}$$

where $ME_{t-1}(n)$ is the total market cap of stock n as of the previous quarter. Therefore, $FIT_t(n)$ is expressed as a fraction of shares outstanding and captures the net demand pressure at time t on stock n from mutual fund flows.

A.1.2 Unexpected Flows and Flow Shocks

Previously anticipated flows should not impact prices. Following Schmickler (2020) and Chaudhary et al. (2023), we construct surprise flows by estimating a fund-specific AR(3) model with time trend for funds with more than 20 quarters of data:

$$f_{j,t} = \alpha_j + \delta_j t + \sum_{k=1}^{3} \phi_{j,k} f_{j,t-k} + \varepsilon_{j,t} \tag{A.2}$$

The unexpected flow is the residual: $f^u_{j,t} = \varepsilon_{j,t}$. For funds with insufficient history, we use raw flows, $f_{i,t}$. Therefore, unexpected flows $f^u_{j,t}$ are defined as the residuals from regressing fund flows on its own lagged flows, a time trend, and a constant. Intuitively, $f_{j,t}^{u}$ measures the unexpected part of the flow given the fund's past.

In addition, we also calculate so-called flow shocks, $f_{i,t}^{shock}$. To do so, we remove the cross-sectional average flow on any given date from raw flows, $f_{i,t}$. Therefore, flow shocks measure how much a fund's flow differs from the typical fund flow on that same date.

Finally, we aggregate these two additional flow measures to $FIT_t^u(n)$ and $FIT_t^{shock}(n)$ according to equation (A.1).

A.2 Variance Ratio Methodology

A.2.1 Lo-MacKinlay Overlapping Estimator

We estimate variance ratios using the overlapping estimator of Lo and MacKinlay (1988). For a series of T log returns $\{r_t\}_{t=1}^{T}$ with aggregation ratio k, define:

Sample mean:

$$\hat{\mu} = \frac{1}{T} \sum_{t=1}^{T} r_t \tag{A.3}$$

One-period variance:

$$\hat{\sigma}_1^2 = \frac{1}{T-1} \sum_{t=1}^{T} (r_t - \hat{\mu})^2 \tag{A.4}$$

k-period overlapping variance:

$$\hat{\sigma}_k^2 = \frac{1}{m} \sum_{t=k}^{T} \left(r_t^{(k)} - k\hat{\mu} \right)^2, \tag{A.5}$$

where $r_t^{(k)} = \sum_{j=0}^{k-1} r_{t-j}$ is the k-period return ending at t, and

$$m = k(T - k + 1) \left(1 - \frac{k}{T} \right) \tag{A.6}$$

is a bias-correction factor that accounts for the reduced degrees of freedom from overlapping observations.

The variance ratio is then:

$$VR(k) = \frac{\hat{\sigma}_k^2}{\hat{\sigma}_1^2}. \tag{A.7}$$

We compute the variance ratio in a backward-looking rolling 12-year window. For each window, we require stocks to have at least 40 consecutive quarters of uninterrupted history ending at the target year.

A.2.2 Cross-Sectional Residualization

For each period t, we run the weighted cross-sectional regression:

$$r_t(n) = \sum_j \beta_{j,t} X_{j,t-1}(n) + IndFE_t(n) + \varepsilon_t(n), \tag{A.8}$$

where $r_t(n)$ is the return for stock n, $X_{j,t-1}(n)$ are lagged characteristics, $IndFE(n)$ are industry fixed effects, and the regression is weighted by lagged market equity. The residuals $\varepsilon_t(n)$ are used for variance ratio computation.

Table A.1 describes the characteristics used in each specification.

Table A.1: **Characteristics for Cross-Sectional Residualization**

Characteristic	Source	Definition	Lag
Size	CRSP	Log Market Equity	1 month
Beta	OAP	Rolling market beta	1 month
Book-to-Market	OAP	December book equity / market equity	Stale (annual)
Momentum	Constructed	Cumulative return months $t-11$ to $t-1$	None
Short-term Reversal	Constructed	Return in month $t-1$	None
Long-term Reversal	Constructed	Cumulative return months $t-36$ to $t-13$	None
Industry FE	Fama-French	48 industry classification	None

A.2.3 Bootstrap Inference

We compute confidence intervals using a stationary bootstrap that accounts for two sources of dependence: cross-sectional clustering within industries and time-series autocorrelation.

Cross-sectional clustering: For each bootstrap iteration, we resample Fama-French 48 industries with replacement. All stocks within a resampled industry are included together, preserving within-industry correlation structure.

Time-series dependence: Within each resampled cluster, we apply the stationary bootstrap of Politis and Romano (1994) with geometrically distributed block lengths. The expected block length is set to $2k$ periods, where k is the aggregation ratio (e.g., 8 quarters for quarterly-to-yearly variance ratios), to capture dependence at the relevant frequency.

We then report 95% confidence intervals based on 500 bootstrapped samples.

A.2.4 Constructing Net Amihud versus Gross Amihud

Amihud illiquidity based on gross volume for stock n in month t is given by

$$\text{Gross Amihud}_{nt} = \frac{1}{D_{nt}} \sum_{d=1}^{D_{nt}} \frac{|r_{nd}|}{\text{Gross Volume}_{nd}}, \tag{A.9}$$

where $|r_{nd}|$ and Gross Volume$_{nd}$ are daily absolute return and daily turnover of stock n on day d. Rather than relying on the original Amihud (2002) measure, which treats the dollar volume of trading (the product of firm size and turnover) as a measure of trading activity, Brennan et al. (2013) uses a measure of illiquidity that relies on turnover as the measure of trading activity and account for firm size effects separately. As Cochrane (2005) pointed out, the Amihud (2002) measure imposes an automatic scaling of illiquidity with firm size, so that 'smaller stocks which have smaller dollar volume for the same turnover (fraction of outstanding shares that trade) are automatically more illiquid. D_{nt} is the number of days with available ratio in month t. The net volume-based version of this measure is given by

$$\text{Net Amihud}_{nt} = \frac{1}{D_{nt}} \sum_{d=1}^{D_{nt}} \frac{|r_{nd}|}{\text{Net Volume}_{nd}}, \tag{A.10}$$

where Net Volume$_{nd}$ is the net volume on day d in month t.[27]

Appendix B Additional Empirical Results

B.1 Further Evidence from the Time Series

Following Campbell et al. (1993), we estimate the following predictive regression of daily stock returns

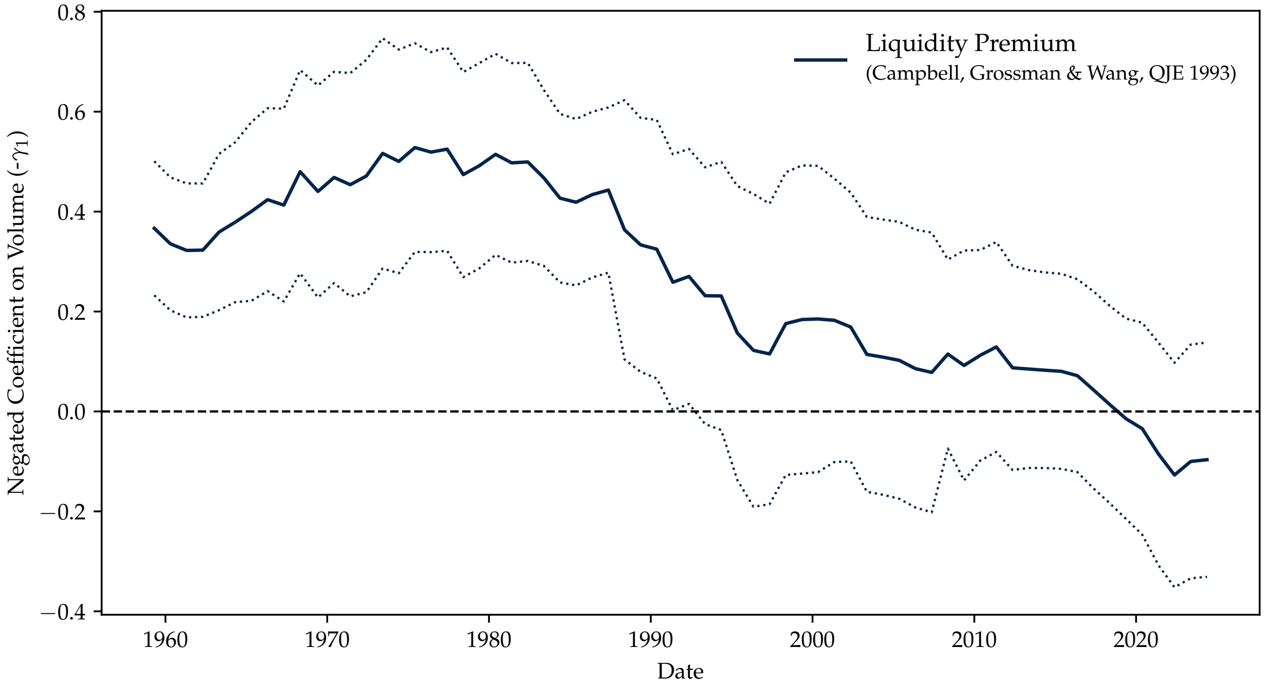
$$r_{t+1} = \alpha + \left(\sum_i \beta_i D_i + \gamma_1 V_t + \gamma_2 V_t^2 + \gamma_3 \sigma_t^2 \right) r_t + \epsilon_t \tag{B.1}$$

where V_t is the detrended log turnover of the aggregate stock market and $\gamma_1 < 0$ captures the premium associated with providing liquidity to high demand shocks. We estimate (B.1) using a rolling 20-year window regressions. Figure B.1 plots the negated coefficient estimate $-\hat{\gamma}_1$, which captures the return compensation for providing liquidity for excess demand shifts (as captured by V_t).

[27] Because net volume is only available quarterly (as opposed to daily), we first transform our quarterly measure to a monthly measure by forward-filling two months and dividing by 63 (to express it in days).

Figure B.1: **CGW Liquidity Premium over Time**

The figure plots the liquidity premium $\hat{\gamma}_1$ from Campbell et al. (1993) estimated via 20-year rolling regressions $r_{t+1} = \alpha + \left(\sum_i \beta_i D_i + \gamma_1 V_t + \gamma_2 V_t^2 + \gamma_3 \sigma_t^2\right) r_t + \epsilon_t$ from 1960 to 2025. Following Campbell et al. (1993) V_t is detrended log turnover. The dotted lines indicate 95% confidence bands from heteroskedasticity robust standard errors.

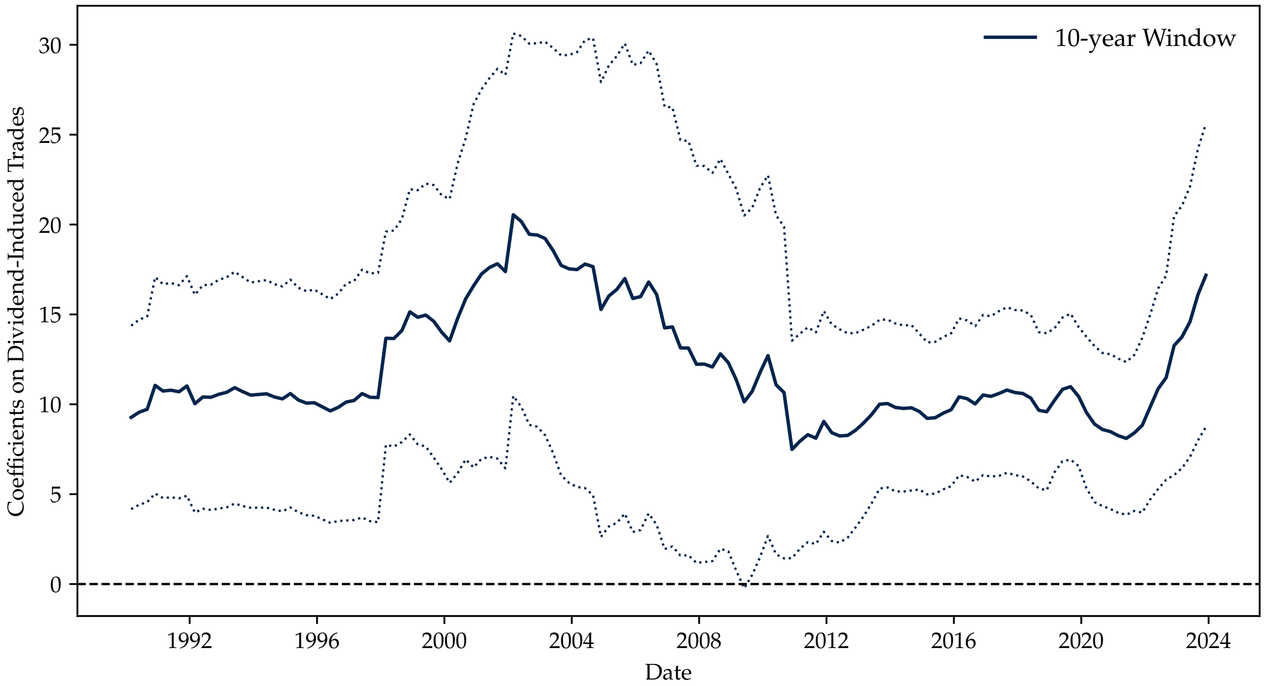


B.2 Dividend-Induced Trades

Because mutual fund flows may reflect investors' information or preferences, flow-induced trades are potentially endogenous. Even after orthogonalizing flows with respect to observable fund characteristics, substantial endogeneity may remain. We therefore also employ an alternative instrument that generates plausibly more exogenous shifts in demand: trading induced by dividend payouts. We closely follow the construction of dividend-induced trades in Schmickler and Tremacoldi-Rossi (2022). Let $D_{t,n}$ denote stock n's dividends per share paid in quarter t. To avoid falling behind their benchmarks, many institutional investors proportionally reinvest the cash from dividend payouts in already-held stocks rather than initiating new positions. An institution's dividend flow in a given quarter, DF_t^i, is given by the total dividend payout across all stocks in the portfolio $DF_t^i = \sum_{n \in N^i} D_{t,n} Q_{t-1,n}^i$ where N^i is the set of stocks held by institution i and $Q_{t-1,n}^i$ the number of shares. The hypothetical trading in a previously held stock due to reinvested dividend flows is given by $DF_t^i w_{t-1,n}^i$. Summing across all institutions and normalizing by (lagged) market equity yields total dividend-induced trades $\text{DIT}_{t,n}$. We regress quarterly returns on dividend-induced trades $\text{DIT}_{t,n}$ using rolling quarterly regressions.

Figure B.2 plots the rolling average of β_t from 1980 to 2024. Just like for flow-induced trades, the average price impact of dividend-induced trades has remained constant since 1980, with no evidence of a secular decline. Table C.2 formally tests for the presence of a time trend in price impact and cannot reject the null hypothesis that impact has remained unchanged since 1980.

Figure B.2: **Relationship between Returns and Dividend-Induced Trades over Time**
The figure plots the estimated coefficients from 10-year rolling windows regressions of quarterly returns onto quarterly dividend-induced trades. The estimated regression coefficients are reported for the period between 1990:Q1 and 2023:Q4.



Appendix C Additional Figures and Tables

Figure C.1: **Case Study: Market Makers and Portfolio Turnover**
The figure plots share of total net volume that is driven by Citadel, Jane Street, Virtu, and Two Sigma (red bars) relative to total net volume averaged across stocks (black bars).

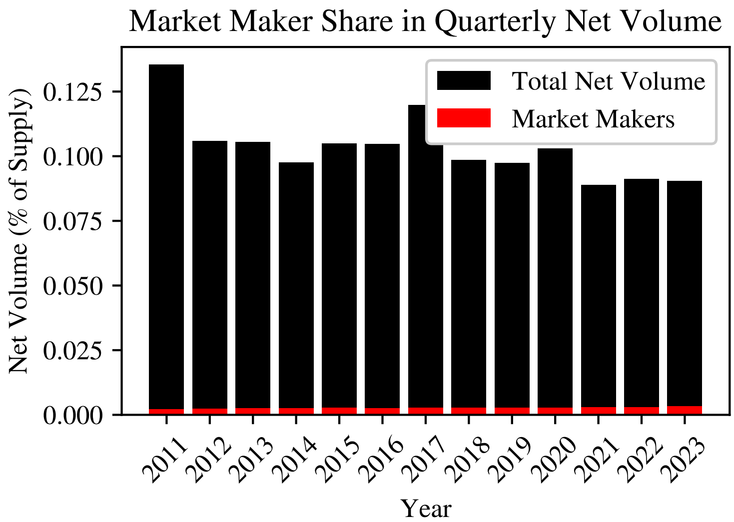


Figure C.2: **Price Impact from Flow-Shocks over Time**
The figure plots the estimated coefficients from 3- and 10-year rolling windows regressions of quarterly returns onto quarterly flow-shock induced trades. Flow shocks are calculated by removing the cross-sectional average flow on any given date from raw flows. The estimated regression coefficients are reported for the period between 1994:Q1 and 2023:Q4.

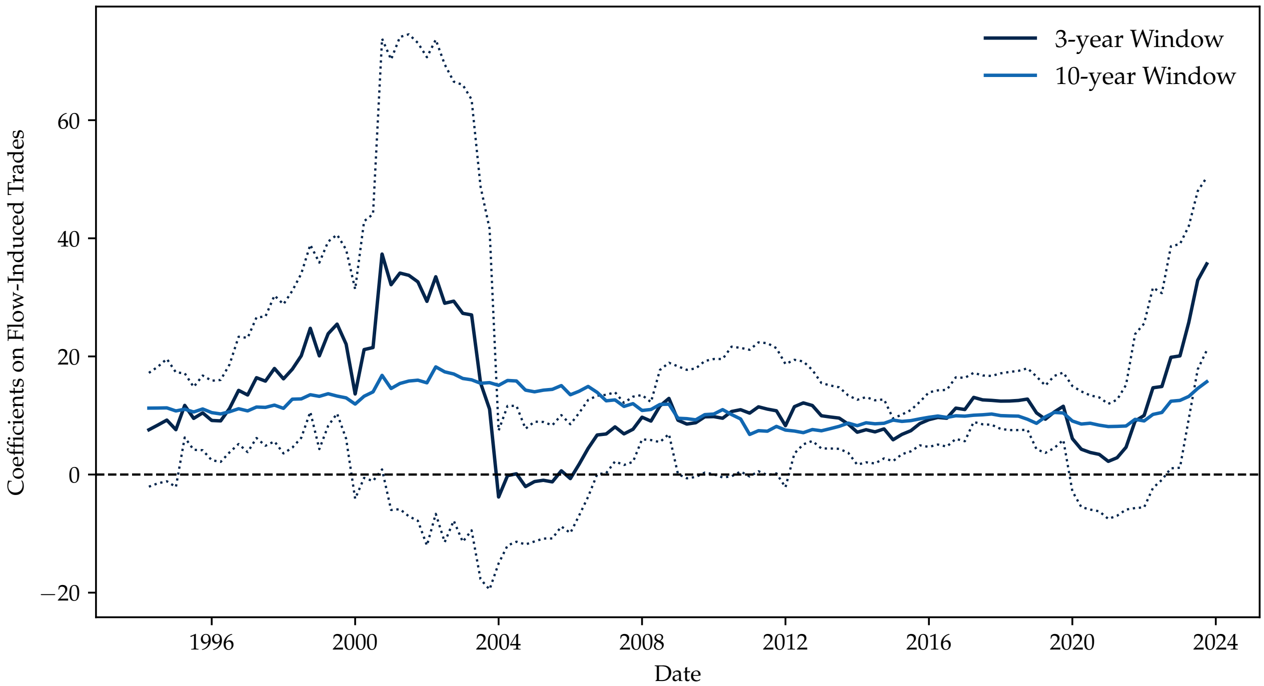


Figure C.3: **Price Impact from Unexpected Flows over Time**
The figure plots the estimated coefficients from 3- and 10-year rolling windows regressions of quarterly returns onto quarterly unexpected flow induced trades. Unexpected flows are defined as the residuals from regressing fund flows on its own lagged flows, a time trend, and a constant. The estimated regression coefficients are reported for the period between 1994:Q1 and 2023:Q4.

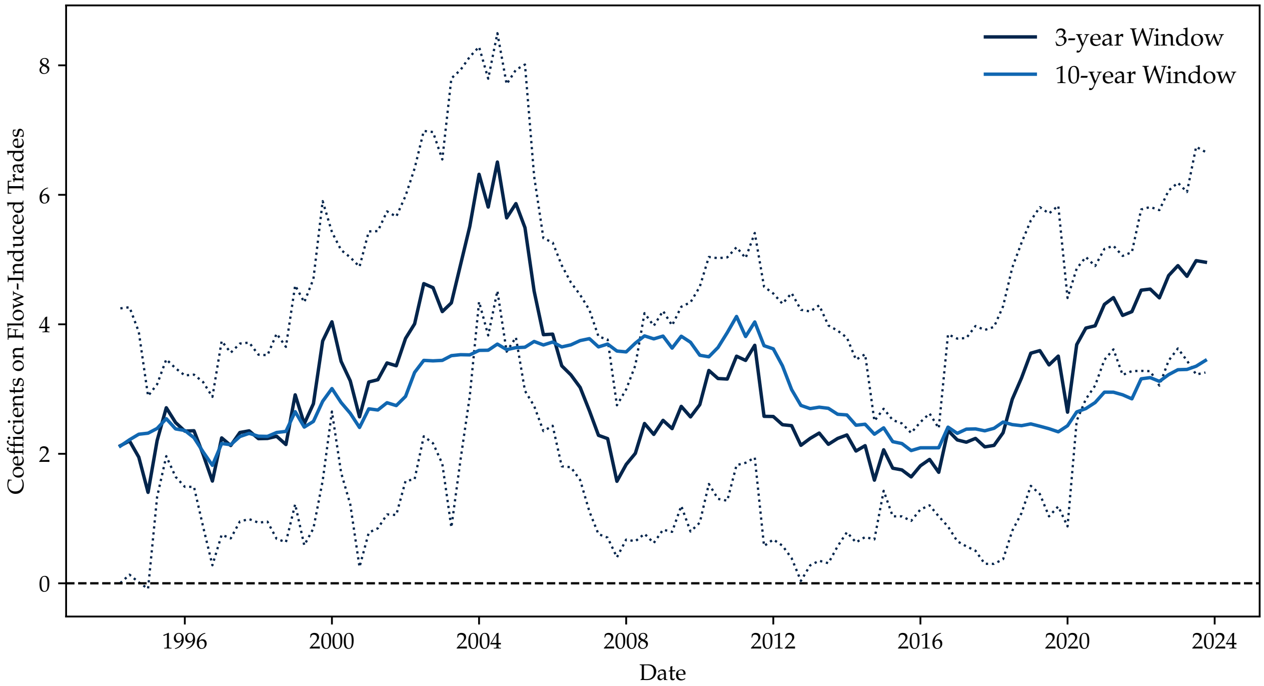


Figure C.4: **Decline of High Frequency Reversal: FMB Regressions**
The figure plots the coefficient obtained from daily Fama-MacBeth regressions of returns onto past three-day cumulative returns, controlling for market beta and lagged (log) market equity. We plot the 10-year rolling average of the coefficient along with 95% confidence intervals (dotted lines).

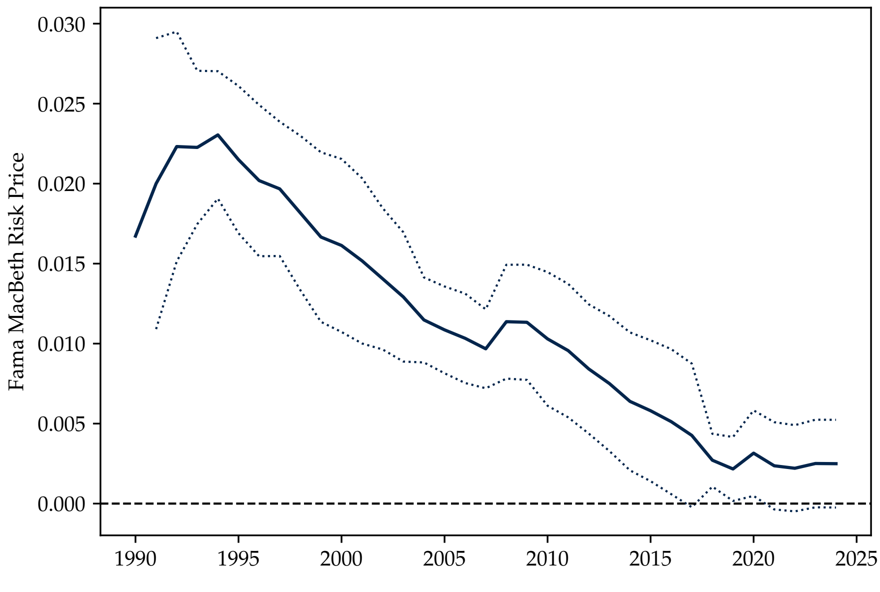
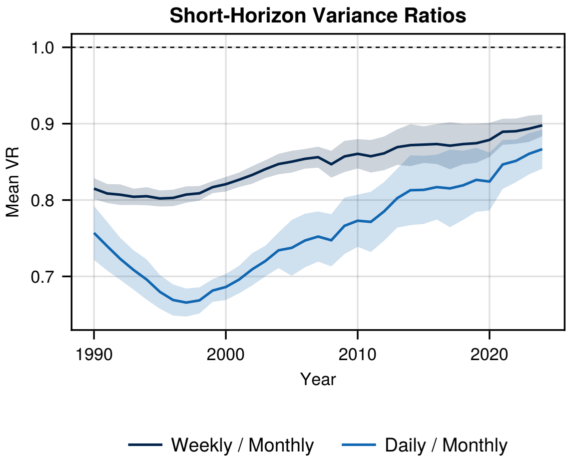


Figure C.5: **Variance Ratios Over Time: Momentum and Reversal Controls**
The figure replicates Figure 10 with abnormal returns additionally residualized against momentum, short-term reversal, and long-term reversal characteristics. Panel (a) shows short-horizon variance ratios (daily-to-monthly and weekly-to-monthly). Panel (b) shows long-horizon variance ratios (daily-to-yearly, monthly-to-yearly, and quarterly-to-yearly). The sample period is 1980–2024. Shaded regions indicate 95% confidence intervals computed using stationary bootstrap clustered by industry.

(a) Short-Horizon Variance Ratios



(b) Long-Horizon Variance Ratios

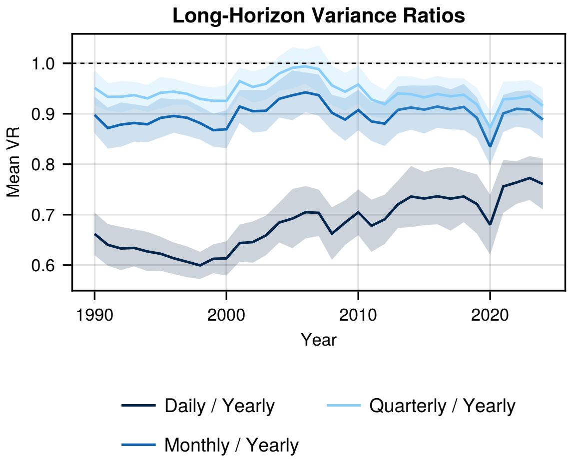


Table C.1: **Variance Ratio Deviation and Round-Trip Trades**
We report regressions of round-trip trades, defined as the (log) difference between gross and net dollar volume, on high-frequency variance ratio deviations. The unit of observation is the stock-day level. Standard errors are clustered by stock and day.

	Roundtrips						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Variance Ratio Dev. (15 seconds)	-9.803***					-7.230***	-2.117***
	(0.082)					(0.089)	(0.041)
Variance Ratio Dev. (1 min)		-7.732***				-3.025***	-1.257***
		(0.077)				(0.044)	(0.026)
Variance Ratio Dev. (5 min)			-3.340***			-0.906***	-0.363***
			(0.083)			(0.023)	(0.012)
Variance Ratio Dev. (15 min)				-0.558***		-0.194***	-0.071***
				(0.028)		(0.008)	(0.004)
Variance Ratio Dev. (30 min)					0.139***	0.027***	0.012***
					(0.011)	(0.004)	(0.002)
Stock	-	-	-	-	-	-	x
Day	x	x	x	x	x	x	x
Observations	9068656	9068656	9068656	9068656	9068656	9068656	9068649
R^2	0.645	0.517	0.135	0.051	0.048	0.697	0.870
R^2 Within	0.628	0.493	0.092	0.003	0.000	0.682	0.138

Significance levels: $*$ p $<$ 0.05, $**$ p $<$ 0.01, $***$ p $<$ 0.001. Format of coefficient cell: Coefficient (Std. Error)

Table C.2: **Long-Term Impact: Time Trends**

The table reports results from regressing quarterly returns onto dividend-induced trades, controlling for the dividend payout ratio. The variables $D(\cdot)$ indicate decade dummies. period is from 1980:Q1 to 2023:Q4. The reported standard errors in parentheses are clustered by date.

	$LNret_Q$			
	(1)	(2)	(3)	(4)
DIT	11.508***	13.246***	13.493***	
	(1.405)	(1.624)	(1.635)	
Dividend Payout Ratio		0.071***	0.073***	0.071***
		(0.020)	(0.021)	(0.021)
DIT × Time Trend			0.187	
			(0.120)	
DIT × D(1980s)				11.050***
				(2.079)
DIT × D(1990s)				14.043***
				(3.854)
DIT × D(2000s)				11.784*
				(5.187)
DIT × D(2010s)				11.552***
				(1.819)
DIT × D(2020s)				30.482**
				(9.563)
Day	x	x	x	x
Observations	811347	731032	731032	731032
R^2	0.165	0.166	0.166	0.166
R^2 Within	0.003	0.004	0.004	0.005

Significance levels: $*$ p $<$ 0.05, $**$ p $<$ 0.01, $***$ p $<$ 0.001.
Format of coefficient cell: Coefficient (Std. Error)

Table C.3: **Flow-Induced Impact: Time Trends**
The table reports results from regressing quarterly returns onto flow-induced trades. *FIT* denotes the ratio of flow-induced trades measured in shares scaled by quarterly shares outstanding. The variables $D(\cdot)$ indicate decade dummies. period is from 1980:Q1 to 2023:Q4. The reported standard errors in parentheses are clustered by date.

	$LNret_Q$		
	(1)	(2)	(3)
FIT	3.006*** (0.498)	3.018*** (0.445)	
FIT × Time Trend		-0.005 (0.043)	
FIT × D(1980s)			4.500 (3.402)
FIT × D(1990s)			2.743*** (0.674)
FIT × D(2000s)			3.935*** (0.548)
FIT × D(2010s)			1.941* (0.757)
FIT × D(2020s)			4.531*** (0.691)
Date	x	x	x
Observations	423911	423911	423911
R^2	0.172	0.172	0.172
R^2 Within	0.002	0.002	0.003

Significance levels: $*$ p $<$ 0.05, $**$ p $<$ 0.01, $***$ p $<$ 0.001. Format of coefficient cell: Coefficient (Std. Error)

Table C.4: **Net Volume and High-Frequency Liquidity: Size Quintiles**
This table reports panel regressions of high-frequency liquidity measures on net volume, controlling for gross trading volume, high frequency order imbalance volatility, firm size and return volatility. We split the sample into ascending size quintiles by market equity (models (1) to (5)). All volume measures are scaled by shares outstanding. High frequency order imbalance volatility ($HFOIV$) is from Bogousslavsky and Collin-Dufresne (2023). All specifications include time and/or stock fixed effects as indicated. Double-clustered standard errors by stock and day are reported in parentheses.

	spread				
	(1)	(2)	(3)	(4)	(5)
Log Market Cap	-2.619***	-1.435***	-0.829***	-0.343***	-0.052***
	(0.206)	(0.059)	(0.033)	(0.018)	(0.006)
Volatility	0.129***	0.121***	0.081***	0.075***	0.070***
	(0.018)	(0.009)	(0.004)	(0.003)	(0.003)
Net Volume	-0.327***	-0.190***	-0.090***	-0.036***	-0.018***
	(0.035)	(0.012)	(0.006)	(0.005)	(0.003)
Daily Gross Volume	-0.250***	-0.106***	-0.028***	-0.009***	-0.004
	(0.020)	(0.007)	(0.003)	(0.002)	(0.003)
Quarterly Gross Volume	-0.460***	-0.211***	-0.076***	-0.034***	-0.008*
	(0.064)	(0.016)	(0.005)	(0.004)	(0.004)
HFOIV	0.128***	0.104***	0.066***	0.059***	0.086***
	(0.008)	(0.005)	(0.003)	(0.003)	(0.004)
Day	x	x	x	x	x
Observations	347870	1434765	1825768	2081111	2335244
R^2	0.142	0.187	0.198	0.160	0.157
R^2 Within	0.124	0.140	0.113	0.073	0.065

Significance levels: $*$ p $<$ 0.05, $**$ p $<$ 0.01, $***$ p $<$ 0.001. Format of coefficient cell: Coefficient (Std. Error)

Table C.5: **Long-Term Impact under Alternative Models**
This Table reports results from regressing quarterly returns onto flow-induced trades (FIT) in Panel (a) and dividend-induced trades (DIT) in Panel (b). The raw demand measures are scaled by quarterly shares outstanding. *Gross FIT* and *Gross DIT* denote the ratio relative to gross volume. Conversely, *Net FIT* and *Net DIT* denote the ratios relative to net volume. The sample period is from 1980:Q1 to 2023:Q4. The reported standard errors in parentheses are clustered by date.

(a) Earlier Sample: 1980–2005

	Log Return (Quarterly)				
	(1)	(2)	(3)	(4)	(5)
$\frac{FIT}{\text{Shrout.}}$	3.418***				2.524***
	(0.446)				(0.462)
$\frac{FIT}{\text{Gross Vol.}}$		0.171***			-0.254***
		(0.040)			(0.054)
$\sqrt{\frac{FIT}{\text{Gross Vol.}}}$			0.106***		-0.031
			(0.018)		(0.054)
$\sigma\sqrt{\frac{FIT}{\text{Gross Vol.}}}$				0.546***	0.633**
				(0.074)	(0.198)
Date	x	x	x	x	x
Observations	234910	234910	234910	226703	226703
R^2	0.140	0.139	0.140	0.144	0.145
R^2 Within	0.002	0.000	0.002	0.008	0.009

Significance levels: $*$ p $<$ 0.05, $**$ p $<$ 0.01, $***$ p $<$ 0.001. Format of coefficient cell: Coefficient (Std. Error)

(b) Later Sample: 2005–2024

	Log Return (Quarterly)				
	(1)	(2)	(3)	(4)	(5)
$\frac{FIT}{\text{Shrout.}}$	3.397***				2.911***
	(0.427)				(0.435)
$\frac{FIT}{\text{Gross Vol.}}$		0.306***			-0.181*
		(0.085)			(0.069)
$\sqrt{\frac{FIT}{\text{Gross Vol.}}}$			0.126***		-0.022
			(0.025)		(0.073)
$\sigma\sqrt{\frac{FIT}{\text{Gross Vol.}}}$				0.571***	0.378
				(0.092)	(0.279)
Date	x	x	x	x	x
Observations	177180	177180	177180	172349	172349
R^2	0.197	0.194	0.195	0.199	0.200
R^2 Within	0.004	0.001	0.002	0.003	0.004

Significance levels: $*$ p $<$ 0.05, $**$ p $<$ 0.01, $***$ p $<$ 0.001. Format of coefficient cell: Coefficient (Std. Error)

Table C.6: **Gross Volume versus Net Volume: Double Sorts**

Every month, portfolios are formed by sequentially sorting stocks using NYSE breakpoints. The table reports portfolios' four-factor value-weighted alpha (in percent). We sort stocks based on gross and net volume. Both measures are scaled by shares outstanding and therefore capture turnover. Panel (a) sorts stocks into quintiles based on net volume, then on gross volume within each net volume quintile. Panel (b) sorts stocks on gross volume then on net volume within each gross volume quintile. Gross volume is the average monthly turnover over the previous month. Net volume is the lagged quarterly net turnover. The sample consists of NYSE, Amex, and NASDAQ common stocks over 1980–2023. t-statistics are reported in parentheses and computed using Newey-West standard errors with six lags. *, **, and *** denote significance at the 10%, 5%, and 1% level.

(c) Net volume then gross volume: α^{EW}_{FF4} (%)

	low gross Vol.	2	3	4	high gross Vol.	H - L
low net Vol.	0.308	0.233	0.393	0.429	0.562	0.255
2	0.068	-0.005	0.184	0.153	0.352	0.283*
3	0.008	0.286	0.047	0.078	0.358	0.349**
4	0.039	0.151	0.180	0.080	0.183	0.145
high net Vol.	0.005	0.168	0.121	-0.083	0.120	0.115

(b) Gross volume then net volume: α^{EW}_{FF4} (%)

	low net Vol.	2	3	4	high net Vol.	H - L
low gross Vol.	0.421	0.181	0.079	0.045	-0.032	-0.452***
2	0.448	0.206	-0.063	0.176	0.125	-0.323**
3	0.494	0.253	0.054	0.142	0.171	-0.323**
4	0.407	0.024	0.127	0.062	0.154	-0.253*
high gross Vol.	0.421	0.288	0.225	0.155	-0.058	-0.479***

Table C.7: **Gross versus Net Amihud: Portfolio Sorts and Fama–MacBeth Regressions**
Panel (a) reports equal-weighted four-factor adjusted average alphas for portfolios based on Gross and Net Amihud illiquidity. Panel (b) estimates monthly Fama-MacBeth regressions of future four-factor (MKT, SMB, HML, and UMD) adjusted returns onto net amihud, gross amihud, and market equity. The reported t-statistics are Newey-West robust with 6 lags.

(a) Gross and net Amihud: α^{EW}_{FF4} (%)

low Gross A	2	3	4	high gross A	H - L
0.017	0.137	0.152	0.184	0.437	0.420***

low Net A	2	3	4	high net A	H - L
0.070	0.198	0.151	0.201	0.408	0.339***

(a) Fama–MacBeth Regressions

	Dependent Variable: Four-Factor-adjusted Returns								
ln(Gross Amihud)	0.261***		0.162*	0.089		0.286***		-0.035	-0.036
	(4.66)		(1.89)	(1.37)		(5.18)		(-0.36)	(-0.38)
ln(Net Amihud)		0.239***	0.170**		0.177***		0.254***	0.224***	0.230***
		(4.60)	(2.11)		(3.49)		(4.96)	(2.58)	(2.83)
ln(Mcap)				-0.179***	-0.177***			-0.181***	-0.211***
				(-7.41)	(-8.51)			(-6.90)	(-6.64)
$Ret[-1]$						-0.043***	-0.042***		-0.045***
						(-3.13)	(-3.07)		(-3.18)
$Ret[-12,-2]$						0.000	0.000		0.001
						(0.14)	(0.01)		(0.36)
Avg. R^2	0.004	0.002	0.006	0.005	0.004	0.052	0.051	0.008	0.057
Avg. Obs	942	935	935	939	935	899	899	935	899

Significance levels: $*$ p $<$ 0.1, $**$ p $<$ 0.05, $***$ p $<$ 0.01.

Table C.8: **Aggregate Stock Market Volume**
The table reports aggregate stock market volume in 2023:Q4 both in dollars and as a fraction of total market equity. We report gross volume, time series net volume (which nets out time-series round-trips) and total net volume (which nets out both time-series and cross-sectional round-trips).

	Dollar Volume (Trillions)	Turnover (%)
Gross Volume	$22.55	50%
Net Volume (xs)	$2.77	6%
Net Volume	$1.33	3%

Table C.9: **Summary Statistics: Variance Ratios**

This table reports summary statistics for the roundtrip trades and variance ratios, expressed as $|\frac{\text{Var}(r_{k,t}(n))}{k\cdot\text{Var}(r_t(n))} - 1|$, at different frequencies. The sample spans 2005–2024. Large- and small-cap stocks are in the top and bottom quintile of market equity in a given quarter.

(a) Large Cap Stocks

		2005	2010	2015	2020
Roundtrips	mean	0.461	0.458	0.364	0.371
	median	0.321	0.352	0.286	0.280
	IQR	0.403	0.301	0.222	0.204
	stdev	0.513	0.425	0.319	0.381
Variance Ratio (15 seconds)	mean	0.149	0.135	0.159	0.149
	median	0.124	0.115	0.137	0.119
	IQR	0.155	0.140	0.179	0.179
	stdev	0.117	0.102	0.117	0.118
Variance Ratio (1 min)	mean	0.142	0.128	0.121	0.109
	median	0.112	0.103	0.098	0.089
	IQR	0.145	0.130	0.124	0.112
	stdev	0.123	0.106	0.101	0.089
Variance Ratio (5 min)	mean	0.218	0.209	0.205	0.193
	median	0.180	0.173	0.171	0.160
	IQR	0.222	0.212	0.210	0.197
	stdev	0.177	0.168	0.163	0.154
Variance Ratio (15 min)	mean	0.265	0.267	0.267	0.264
	median	0.228	0.230	0.228	0.229
	IQR	0.274	0.276	0.275	0.272
	stdev	0.197	0.199	0.200	0.195
Variance Ratio (30 min)	mean	0.289	0.294	0.297	0.300
	median	0.255	0.260	0.263	0.267
	IQR	0.304	0.309	0.311	0.313
	stdev	0.204	0.207	0.207	0.208

(b) Small Cap Stocks

		2005	2010	2015	2020
Roundtrips	mean	0.297	0.223	0.310	0.427
	median	0.178	0.128	0.159	0.198
	IQR	0.262	0.170	0.267	0.317
	stdev	0.489	0.352	0.601	1.190
Variance Ratio (15 seconds)	mean	0.513	0.522	0.501	0.504
	median	0.521	0.528	0.509	0.516
	IQR	0.120	0.126	0.126	0.128
	stdev	0.099	0.102	0.105	0.110
Variance Ratio (1 min)	mean	0.447	0.481	0.449	0.458
	median	0.466	0.499	0.463	0.481
	IQR	0.234	0.222	0.235	0.248
	stdev	0.170	0.165	0.170	0.179
Variance Ratio (5 min)	mean	0.317	0.354	0.334	0.354
	median	0.294	0.343	0.309	0.327
	IQR	0.317	0.328	0.338	0.378
	stdev	0.208	0.211	0.218	0.230
Variance Ratio (15 min)	mean	0.288	0.283	0.288	0.300
	median	0.248	0.245	0.248	0.266
	IQR	0.299	0.296	0.303	0.311
	stdev	0.212	0.206	0.214	0.212
Variance Ratio (30 min)	mean	0.298	0.287	0.284	0.286
	median	0.258	0.246	0.239	0.243
	IQR	0.318	0.310	0.313	0.315
	stdev	0.215	0.211	0.214	0.213