Rethinking Volume: Has the Market Become More Liquid?*

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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 its reversal 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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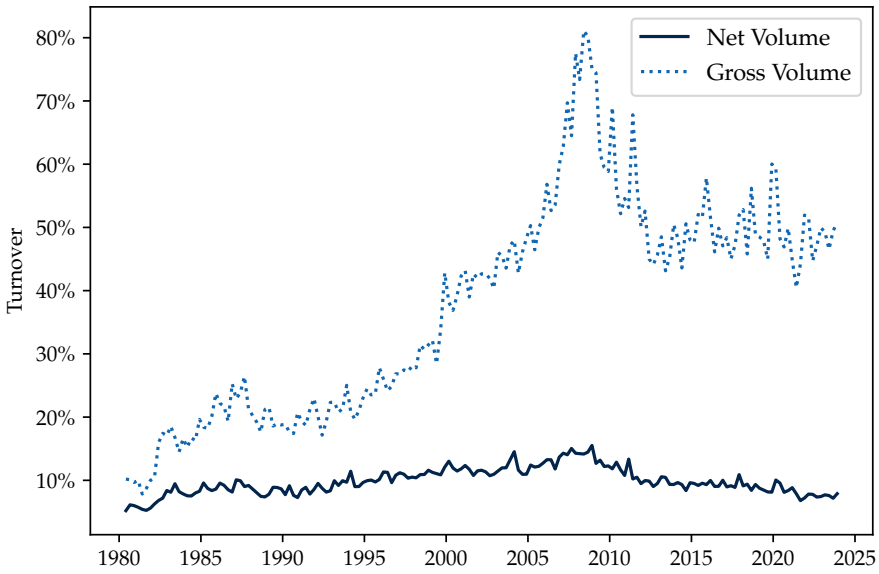
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1 Introduction

Over the past four decades, gross trading volume in equity markets has risen sharply. In 1980, the median stock turned over about 10% of its shares outstanding every quarter; by 2000, turnover reached 30% per quarter, and by 2024 it exceeded 50%. 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 long-term 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 ther largest 2000 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. So have financial

market become more liquid? Yes, but only in the short term.

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.

Any argument about trends in liquidity requires a clear definition of both the concept and the horizon. We define liquidity as the inverse of the price impact of a non-fundamental demand shift for a financial asset. We distinguish between two horizons: short-term, corresponding to daily or intraday frequencies, and long-term, corresponding to *quarterly* frequencies. This distinction matters because the forces driving liquidity at each horizon are fundamentally different. Short-term price impact captures transient dislocations absorbed by high-frequency intermediaries, while long-term price impact reflects the market's capacity to absorb persistent portfolio reallocations precisely the reallocations measured by net volume.

With these definitions in hand, our main findings are as follows. Consistent with the stability of quarterly 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 and show that it 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.

We furthermore show that self-reported mutual fund portfolio turnover is quantitatively closely aligned with our net volume measure. Reconstructing portfolio turnover from quarterly filings, we find that mutual funds engage in very little within-quarter round-trip trading. Moreover, their portfolio turnover has declined since 2000, reinforcing the conclusion that the growing wedge between gross and net volume is driven by a different class of market participants operating at much higher frequencies. We argue that gross volume is contaminated by cumulated round-trip trades from high-frequency intermediaries, making it a considerably noisier measure of net trading activity at longer horizons. We provide an intuitive example by showing that the 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.[1]

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

[1]Consistent with Chordia et al. (2005), who show that high-frequency trading eliminates intraday return autocorrelation by absorbing order imbalances within 60 minutes, we further document that round-trip tradesmeasured as the gap between gross and net volumeare strongly correlated with variance ratios at *intraday* frequencies, suggesting that the bulk of round-trip trading occurs at relatively short horizons.

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.[2] 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.[3] To show that the impact from these long-term demand shocks indeed measures illiquidity as opposed to price discovery, we show that the majority of the quarterly impact reverts over the following year and that the amount of reversal has remained unchanged since 1990.

We then reconcile the declining short-term impact and constant long-term impact by assessing reversal patterns across horizons. First, the sharpe ratio and abnormal 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. The sharpe ratio and abnormal returns to a long-term reversal strategies on the other hand have remained remarkably stable over time. 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

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

[3]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.

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 volume – are highly effective at redistributing risk but do not bear it over long horizons.[4]

To corroborate our claim that long-term price impact has remained unchanged, we benchmark net volume against gross volume in 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.[5] 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 show that net trading volume contains incremental information for return predictability

[4]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.

[5]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.

beyond gross volume in the cross-section of U.S. stocks. Without taking a stance on whether volume 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 far less liquid than suggested by gross trading volume. Even small flows can generate substantial price impact, consistent with Gabaix and Koijen (2021), who find that a 1% inflow relative to total market equity leads to a 5% return. These magnitudes appear much more natural in light of low net volume: quarterly net volume at the market level is approximately 2.5% of market equity, so a 1% inflow represents roughly 40% of effective supply (net volume), lending support to the magnitude of their estimates. van der Beck et al. (2025) use net volume measure to derive an explicit bound on price impact, conditional on investor disagreement.[6] 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

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

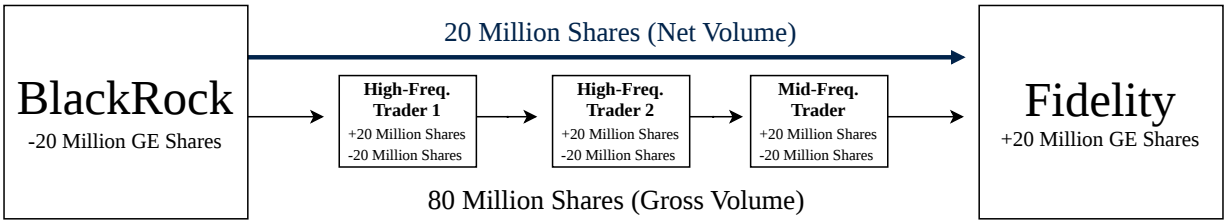
market. Section 6 concludes.

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.[7] 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

[7] 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).[8] 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.[9]

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

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

[8] All results are robust to the subset of stocks that have (on average) at least 50% observed institutional ownership.
[9] 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 institutions 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	0.062	0.092	0.130	0.110	0.097
	median	0.048	0.073	0.112	0.091	0.077
	IQR	0.058	0.078	0.096	0.077	0.062
Gross Volume	mean	0.176	0.337	0.638	0.632	0.680
	median	0.124	0.191	0.470	0.483	0.472
	IQR	0.151	0.272	0.543	0.446	0.418
CS Corr. ρ(Net,Gross)		0.484	0.618	0.654	0.611	0.642
TS Corr. ρ(Net,Gross)		0.125	0.146	0.225	0.206	0.225

(b) Large Cap Stocks

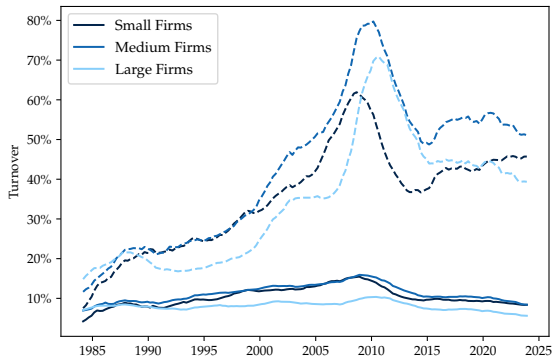
		1980	1990	2000	2010	2020
Net Volume	mean	0.073	0.083	0.103	0.087	0.068
	median	0.060	0.067	0.088	0.073	0.058
	IQR	0.046	0.052	0.062	0.052	0.036
Gross Volume	mean	0.179	0.265	0.598	0.572	0.536
	median	0.141	0.170	0.428	0.471	0.401
	IQR	0.119	0.151	0.452	0.327	0.266
CS Corr. ρ(Net,Gross)		0.516	0.632	0.616	0.618	0.643
TS Corr. ρ(Net,Gross)		0.160	0.136	0.185	0.233	0.278

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.

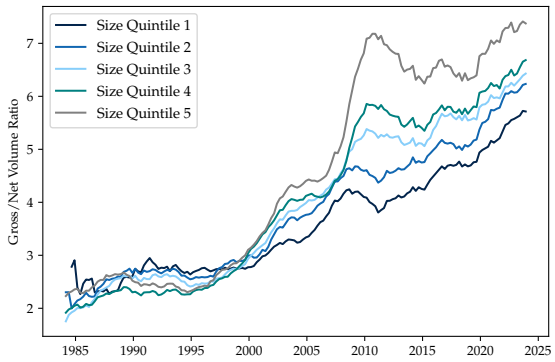
Panel (a) of Figure 3 plots gross and net trading volume across the size distribution of U.S. stocks. The widening divergence between gross and net volume is present for firms of all sizes. Across the size distribution, gross trading volume has increased sharply while net trading volume, which captures 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.

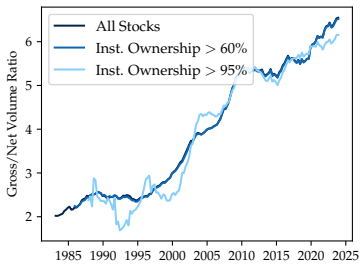
First, we verify that the gap between gross and net volume is not driven by large trades within the unobserved non-13F sector. Panel (a) of Figure 4 plots the ratio of gross trading volume to portfolio turnover for the full sample and for subsamples restricted to stocks with institutional ownership above 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.

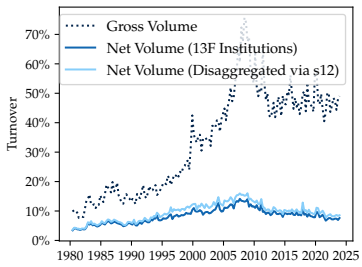
Second, we verify that the gap between gross and net volume is not driven by aggregation across investors. In principle, large offsetting trades across mutual funds within a quarter could net out when holdings are reported at the asset-manager level in the 13F data, mechanically reducing measured net 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).[10] 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.

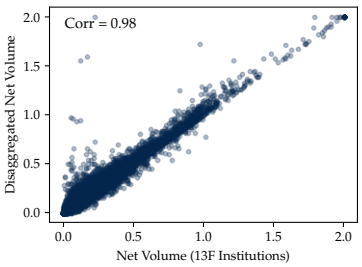
(a) Omitted Investors



(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

[10]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 Mutual Fund Portfolio Turnover versus Net Volume

While roundtrip trading is inherently difficult to observe from slow-moving portfolio holdings, mutual funds offer a setting where this is possible at the fund level, as mutual funds report their annual portfolio turnover ratio. The turnover ratio is a mandatory filing under the Investment Company Act of 1940 and measures the minimum of aggregated sales or purchases divided by average 12-month total net asset value. Earlier studies on mutual funds report *annual* turnover measures of 70-100% (Carhart, 1997; Wermers, 2000; Baker et al., 2010). How have these numbers evolved since, how do they compare to net volume quantitatively, and how much of this turnover is driven by roundtrip trading within quarters?

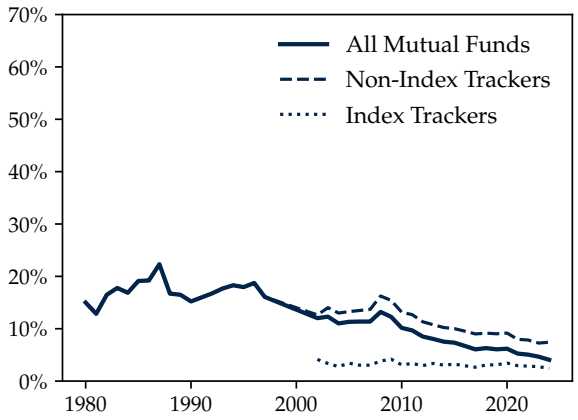
Panel (a) of Figure 5 plots the AUM-weighted average turnover ratio across all funds since 1980. Turnover is reported at the annual level; we divide by 4 to express it in quarterly units for comparability with our other volume measures. Unlike gross volume, which has steadily increased over time, mutual fund turnover has slightly *decreased*, particularly since 2000. Part of this decline comes from the growth of index-tracking mutual funds. However, even non-index trackers decreased their turnover. Furthermore, the magnitudes are in line with our net volume measures: average quarterly turnover is around 10% — close to our average net volume over time. We next merge the fund-level data with portfolio holdings and construct the same turnover measure from the funds' quarterly filings.[11] Any difference between reported and holdings-based turnover is due to roundtrip trading within quarters. Panel (b) compares, for each fund, time-series averages of the two turnover measures over the cross-section of funds. The two are highly correlated and lie close to the diagonal, indicating that within-quarter roundtrip trading plays a minor role. Within-quarter roundtrip trading becomes more important for more active funds. However, even for the most active funds with quarterly turnover ratios of 40%, turnover from quarterly filings reaches 30%. This implies that active funds do not contribute much

[11] Formally, for each fund we construct the turnover ratio from portfolio holdings as $\frac{\min\left(\sum_n \Delta Q_t^{(+)}(n)\bar{P}_t(n), -\sum_n \Delta Q_t^{(-)}(n)\bar{P}_t(n)\right)}{\text{Avg. Total Net Assets}_t}$ where $\Delta Q_t^{(+)}$ and $\Delta Q_t^{(-)}$ are positive and negative holdings changes between two quarters and $\bar{P}_t(n)$ is the average price between beginning and end of quarter. We focus on domestic equity mutual funds where assets constructed from quarterly holdings are between 50% and 150% of reported total net assets.

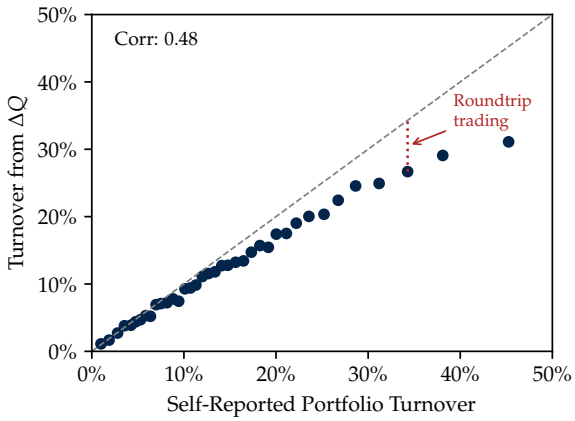
to the rise in gross volume over time. Overall, the data on mutual fund turnover is consistent with our net volume measure, suggesting that trades *inferred* from self-reported portfolio holdings provide a reasonable proxy for the actual trading activity of longer-term investors. This greatly alleviates concerns that inferred trading data from quarterly filings gives a misleading picture of true trading activity due to window dressing, strategic misreporting, or stale and delayed filings.

Figure 5: **Mutual Fund Turnover and Roundtrip Trades**
Panel (a) plots self-reported mutual fund turnover ratio (obtained from CRSP) across all mutual funds, and split by index-tracking versus non-index. The turnover ratio is defined as the minimum of aggregated sales or aggregated purchases of securities divided by average 12-month total net asset value. We plot the AUM-weighted averages expressed in quarterly units. Panel (b) is a binned scatter plot that compares mutual fund turnover ratio to the same turnover ratio constructed from quarterly portfolio holdings $\Delta Q_t(n)$.

(a) Quarterly Portfolio Turnover



(b) Quarterly Roundtrip Trading



2.7 The Frequency of Round-trip Trades

At what frequency does the growing gap between gross and net volume arise? The previous section showed that mutual funds do not account for the growth in gross volume and that even the most active funds engage in little within-quarter roundtrip trading. This suggests the gap perhaps arises at frequencies considerably higher than those at which most mutual funds operate. 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.

Several 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% 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 (SEC, 2014; Hendershott and Riordan, 2013). Baron et al. (2019), Brogaard et al. (2014a), and Hirschey (2021) document that HFTs hold positions for seconds to minutes and unwind the vast majority of their inventory within the trading day, suggesting that a substantial share of round-trip trading occurs at very short horizons. The timing of the growth in algorithmic trading coincides with the widening gap between gross and net volume documented in Figure 1. Third, in Appendix B.1, we show that the cross-sectional variation in the gap between gross and net volume is strongly correlated with variance ratios at intraday frequencies, suggesting that most round-trip trading unwinds within the trading day and contributes to price efficiency at short 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

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

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

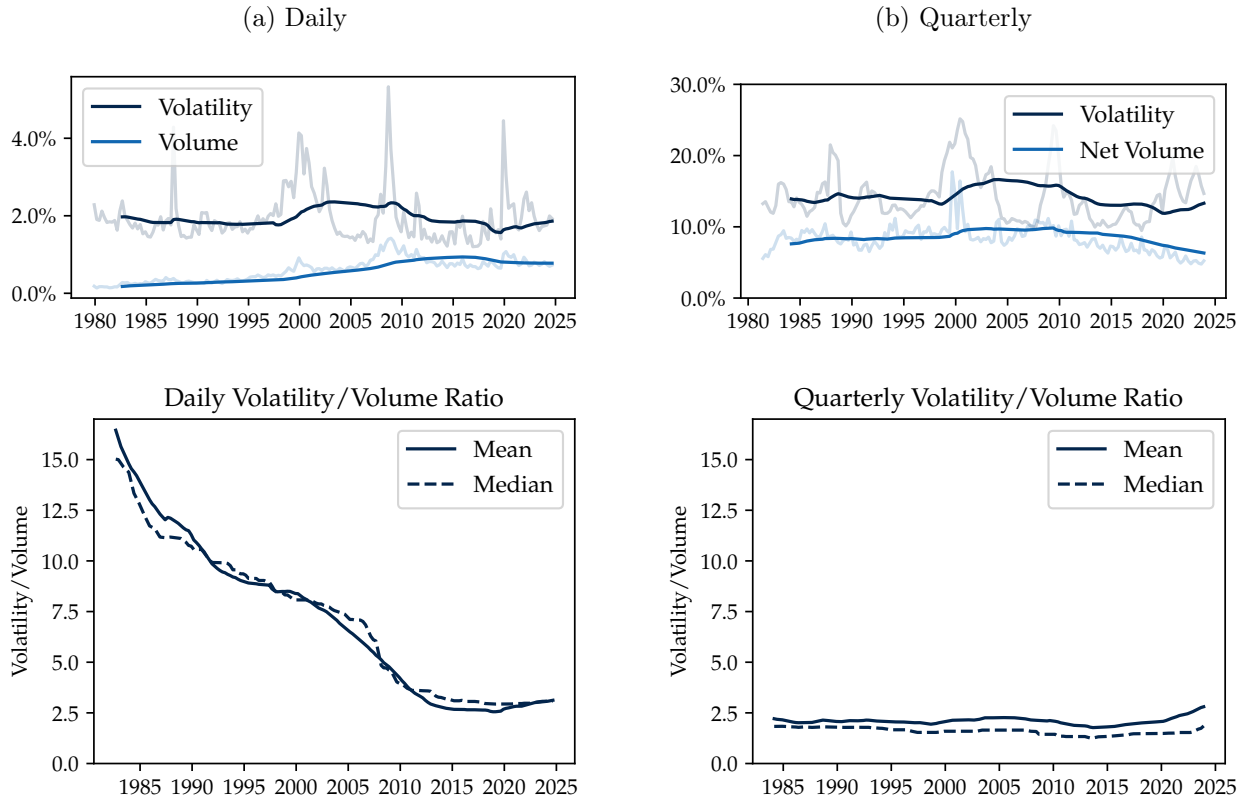
evidence from a structural model of long-term impact.

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.

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.



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.

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 illiquidityit 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

[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

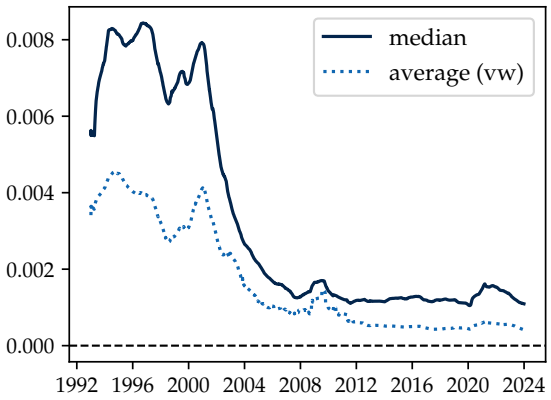
the time-series evolution of investor agreement – for example using analyst beliefs – is an important direction for future research, but goes beyond this simple qualitative motivation.

3.2 High-Frequency Liquidity Has Improved

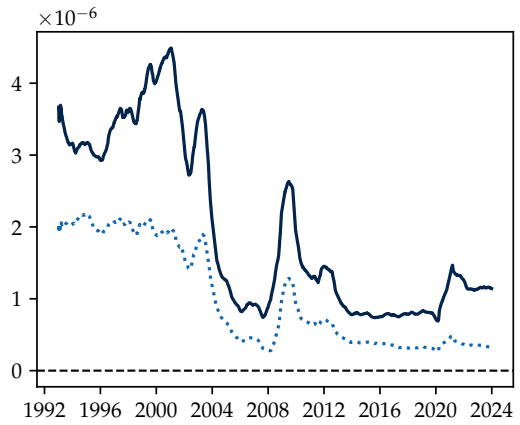
Consistent with the qualitative argument above, we show that the rise in short-horizon trading volume has indeed coincided with considerable improvements in high-frequency liquidity, echoing prior findings (Chordia et al., 2008; Hendershott and Riordan, 2013; Menkveld, 2013; Brogaard et al., 2014b). 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)



common (and thus hidden from net volume).

[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.4. 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:

$$r_t(n) = \alpha_t + \beta_t \text{FIT}_t(n) + \text{Controls} + \epsilon_t(n), \tag{2}$$

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 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.2, 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.4, we show that the same result obtains using our alternative instrument—dividend-induced trades—that generates plausibly more exogenous shifts in demand.

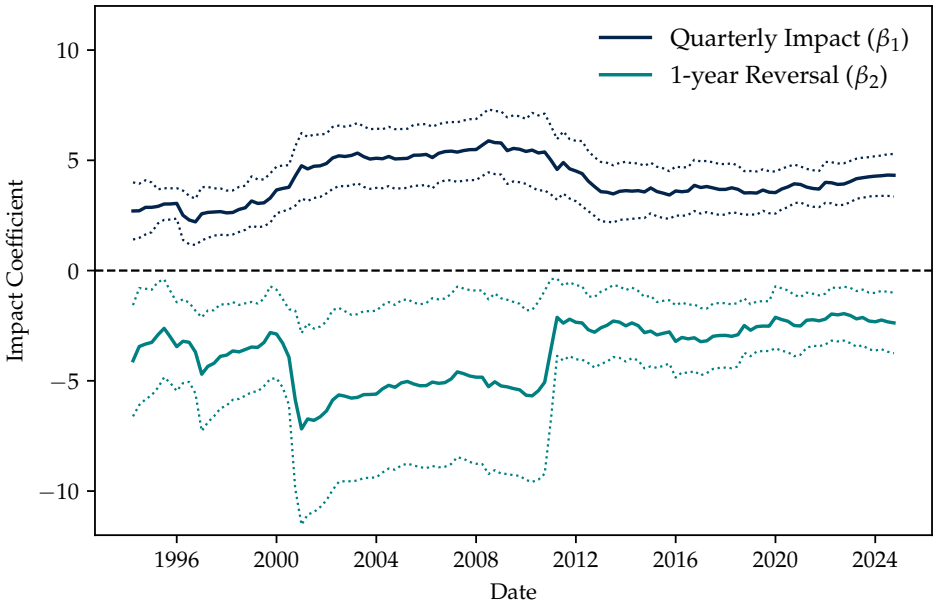
3.4 Reversal of Long-Term Price Impact Has Not Changed

One might argue that our finding of stable long-term price impact simply reflects that long-term impact has always been zero (both in 1990 and now) and that flow-induced trades capture price discovery rather than true price pressure. If this were the case, however, we would not expect the price impact of flow-induced trades to revert. We therefore test whether the price impact of flow-induced trades reverts, and whether this reversal has changed over time. To this end, we estimate

$$r_t(n) = \alpha_t + \underbrace{\beta_{1,t}\text{FIT}_t(n)}_{\text{Impact}} + \underbrace{\beta_{2,t}\overline{\text{Lag-FIT}}_t(n)}_{\text{Reversal}} + \epsilon_t(n), \tag{3}$$

where $\overline{\text{Lag-FIT}}_t = \frac{1}{4}\sum_{l=1}^{4} \text{FIT}_{t-j}$ are flow-induced trades averaged over the previous four quarters. $\beta_{1,t}$ measures the contemporaneous quarterly impact, while $\beta_{2,t}$ average reversal over the following year. We estimate 3 using 10-year rolling windows from 1980 to 2024 and report the impact and reversal coefficients in Figure 9. This specification provides a more powerful test of long-term reversal than simply regressing cumulative future returns on current flows, as it accounts for the autocorrelation of flow-induced trades across quarters. Nevertheless, in Appendix Table C.3 we also report the regressions of flow-induced trades onto future cumulative returns and a granular specification that estimates a separate coefficient on each lag in equation 3: $\sum_{l=1}^{4} \beta_{l,t}\text{FIT}_{t-j}$. Both yield similar reversal patterns, though the cumulative future return specification yields a somewhat weaker reversal pattern due to the positive autocorrelation of flows.

Figure 9: **Long-Term Reversal of Flow-Induced Price Impact**
The figure plots the estimated coefficients from 10-year rolling windows regressions of quarterly returns onto contemporaneous quarterly flow-induced trades as well as the past 4-quarter average of flow-induced trades: $r_t(n) = \alpha_t + \beta_{1,t}\text{FIT}_t(n) + \beta_{2,t}\overline{\text{Lag-FIT}}_t(n) + \epsilon_t(n)$,. The impact coefficient β_1 is reported in blue and the reversal coefficient β_2 in green. The estimated regression coefficients are reported for the period between 1994:Q1 and 2023:Q4.



The figure highlights two main takeaways. First, there is economically meaningful and statistically significant reversal over the following year. The average impact coefficient is 4.3 and the one-year reversal coefficient is −3.4, both highly statistically significant., i.e., on average, roughly 75% of flow-induced price impact reverts in the year after the shock. Second, and more importantly, there are no meaningful trends in the long-term reversal of flow-induced demand shocks. Both the initial impact and its one-year reversal are roughly stable over time, and one cannot statistically distinguish the 1990

estimates from the 2020 ones.

3.5 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 markets 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 markets ability to absorb long-term shifts in fundamental demand.[16]

3.6 Returns to Liquidity Provision

Liquidity providers take the other side of demand shifts by market participants. If this service is compensated through expected returns, the price impact of demand shifts should decay over time: a buy order intermediated by a liquidity provider pushes prices up, generating negative future expected returns that compensate the liquidity provider's short position. One natural definition of liquidity is the size of this compensation the expected returns earned by liquidity-providing strategies. In the classic Grossman and Miller (1988), for example, liquidity providers earn compensation for matching asynchronously arriving buyers and sellers, and competition among market makers drives down the returns to liquidity provision. More generally, an illiquid market is one in which liquidity providers require large compensation, leading to larger initial price impacts of nonfundamental demand shocks that subsequently mean-revert producing predictable patterns in abnormal returns. In a liquid market, such mean reversion should be less pronounced.

This gives rise to a natural test. If long-term liquidity has remained unchanged while short-term liquidity has increased, then returns to high-frequency liquidity-providing strategies should have declined, whereas returns to liquidity provision at longer horizons should have remained unchanged. Since improved short-horizon liquidity is already well-documented, we simply follow Nagel (2012) and construct the daily returns to a high-frequency reversal strategy that weights stocks inversely based

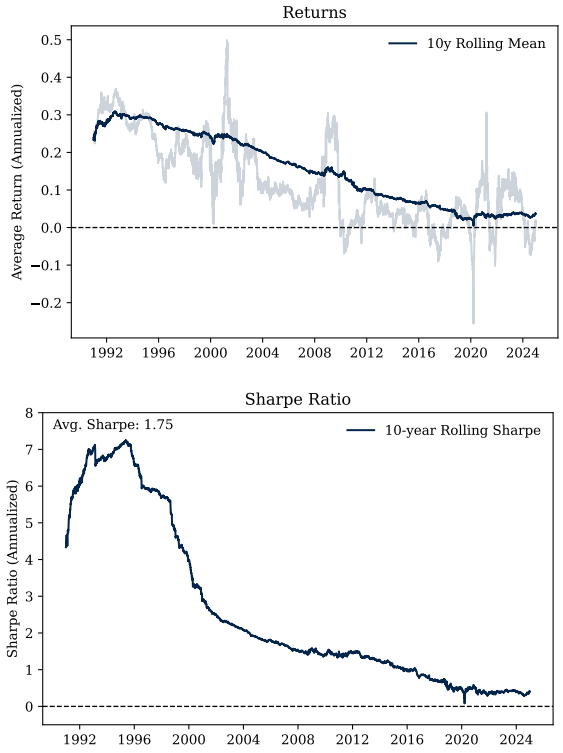
[16] In Section 4, we show that quarterly net volume (as opposed to gross volume) does contain incremental information about long-term price impact beyond shares outstanding.

on their prior five days returns. Panel (a) of Figure 10 plots the average returns alongside the 10-year rolling Sharpe ratio from the high-frequency reversal strategy. In the early part of our sample, the strategy delivered extraordinarily high annualized Sharpe ratios exceeding 7, consistent with the findings of Nagel (2005). However, the profitability of short-term liquidity provision has declined systematically over time. The decline is stark: the annualized Sharpe ratio falls from roughly 7 in the 1990s to approximately 0.4 in recent years, mirroring the well-documented improvement in short-horizon liquidity. 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.

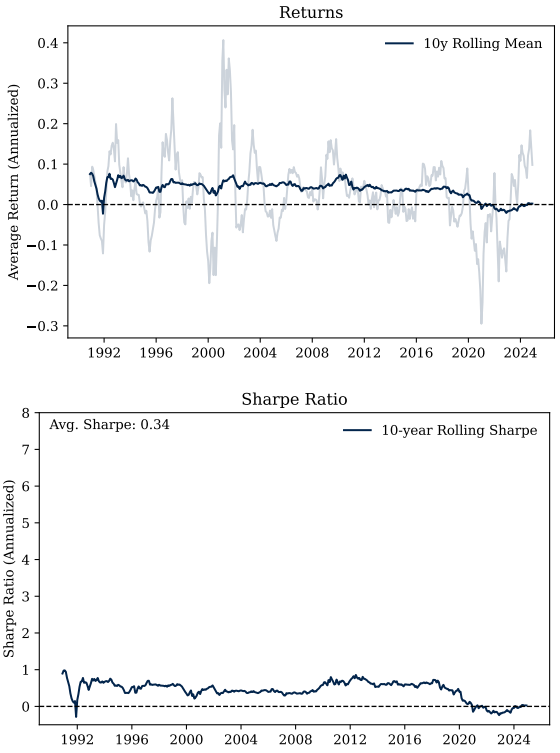
Next, we estimate the returns to low-frequency liquidity provision. To this end, we construct a long-term reversal strategy using the same long-short weighting scheme as for the high-frequency strategy, but now stocks are weighted inversely based on their average flow-induced trades over the past four quarters. We use flow-induced trades rather than simple past returns because returns over longer horizons are dominated by fundamental news that should not revert. Indeed, weighting stocks based on past returns yields negative returns to the reversal strategy simply recovering the 12-month momentum effect (Jegadeesh and Titman, 1993). Panel (b) of Figure 10 plots the moving average of monthly returns and the rolling 10-year sharpe ratio from this strategy over time. Unlike its high-frequency counterpart, the strategy's returns that have remained remarkably stable throughout our sample period, with an annualized Sharpe ratio of approximately 0.34. The overall pattern is clear: over the period in which gross trading volume increased dramatically, only the returns to short-term liquidity provision have declined, while the returns to long-term liquidity provision are largely unchanged in line with our hypothesis of unchanged long-term liquidity.

Figure 10: **Trends in the Returns to Liquidity Provision**
Panel (a) plots the 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 returns on days $t-1, ..., t-5$ and a holding period of 1 day post formation. Panel (b) plots the returns to a simple long-term reversal strategy with weights proportional to (negated) of average past 4-quarter flow-induced trades $\overline{\text{Lag-FIT}}_t(n)$ and a holding period of 1 quarter post formation. For all strategies 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 the returns respectively.

(a) High Freq. Liquidity Provision



(b) Low Freq. Liquidity Provision



Note that stocks with sustained flow-induced buying may become overvalued and trade at low book-to-market ratios, so the low-frequency strategy's returns may partly reflect value exposure. In fact value investing can itself be viewed as a form of long-term liquidity provision. To test for exposure to known pricing factors, Table 2 reports annualized Fama-French three-factor alphas and factor loadings for both strategies. The high-frequency reversal strategy earns a large alpha of approximately 13% per annum over the full sample, but this has declined markedly: in the post-2010 subsample, the alpha falls to 4.7% per year. The strategy loads significantly on market risk but shows little exposure to size or value. The low-frequency reversal strategy has fundamentally different factor exposures. It delivers a significant annualized alpha of approximately 3% (t-statistic of 2.01) and, in line with the intuition above, loads significantly on value (t-statistic of 2.7). Importantly, however, the alpha is not subsumed by this value exposure, indicating that betting against flow-induced trading captures a distinct source

of return beyond conventional value.[17]

Table 2: **Abnormal Returns: Liquidity Provision Strategies**
This table reports annualized average returns, annualized Sharpe ratios, and Fama-French three-factor regression estimates for the high-frequency (HF) and low-frequency (LF) liquidity provision strategies. The HF strategy is the daily reversal portfolio constructed form past 5-day returns. The LF strategy is the quarterly reversal portfolio constructed from past 4-quarter flow-induced trades $\overline{\text{Lag-FIT}}_t(n)$. Factor regressions use daily and monthly Fama-French factors for the HF and LF strategies respectively. Alphas are annualized. The sample runs from 1980 to 2024, with subsample splits for the HF strategy at 2010. Newey-West standard errors are reported in parentheses.

	Avg Ret	Sharpe	α	β^{Mkt}	β^{SMB}	β^{HML}
High Freq. (all)	13.00	1.75	12.17	0.11	0.03	-0.04
			(1.14)	(0.01)	(0.02)	(0.02)
High Freq. (pre-2010)	17.96	2.65	17.72	0.09	0.05	-0.09
			(1.39)	(0.02)	(0.03)	(0.04)
High Freq. (post-2010)	4.80	0.58	3.53	0.11	-0.01	-0.03
			(1.90)	(0.02)	(0.04)	(0.03)
Low Freq.	3.19	0.34	2.91	-0.01	-0.13	0.30
			(1.45)	(0.05)	(0.06)	(0.11)

3.7 Variance Ratio Tests Across Horizons

Variance ratios provide a complementary test of mean reversion in stock returns and are widely used as indicators of market liquidity and efficiency (Lo and MacKinlay, 1988; Poterba and Summers, 1987; Chordia et al., 2011). Relative to the reversal strategies above, they offer a more powerful test of serial dependence, as they exploit the full time series of returns and aggregate autocorrelation information across horizons. The trade-off is that they measure serial correlation in returns generally, rather than reversion to a specific demand shock. We present them here as an additional piece of evidence.

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

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

We consider four frequency pairs spanning short and long horizons: daily-to-monthly ($k = 21$), weekly-to-monthly ($k = 4$), 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.[18] When abnormal returns follow random walks, $VR_k(n) = 1$. A variance ratio below

[17] Whether the value factor itself partly reflects long-term liquidity provision as our framework suggests or compensation for fundamental risk is not a distinction we aim to resolve. Following Kozak et al. (2018), what matters for arbitrageurs is that any source of comovement, regardless of its origin, constitutes arbitrage risk and commands a premium.

[18] 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.

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.[19] We also include Fama-French 48 industry fixed effects to further absorb common variation. The regression residuals constitute our abnormal returns.[20]

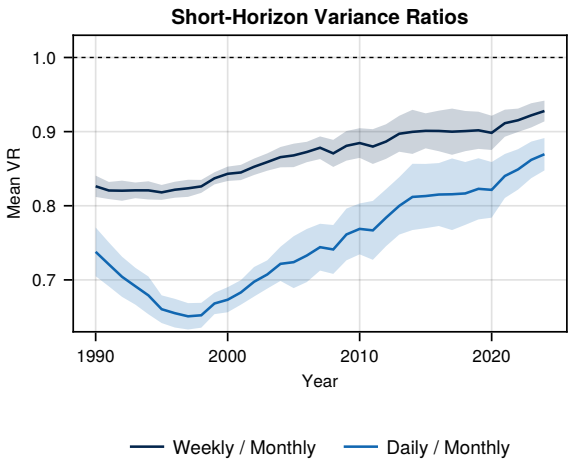
For each stock-year, we estimate $VR_k(n)$ using the overlapping estimator of Lo and MacKinlay (1988) over rolling 12-year windows. Confidence intervals are computed using a stationary bootstrap that accounts for both cross-sectional clustering by industry and time-series dependence (see Appendix A.2 for details). Figure 11 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. Panel (b) presents variance ratios at longer horizons. In contrast to the steady increase in short-horizon variance ratios in Panel (a), 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 quarterly-to-yearly variance ratio hovers around 0.95, and if anything, has slightly declined.

[19] 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.

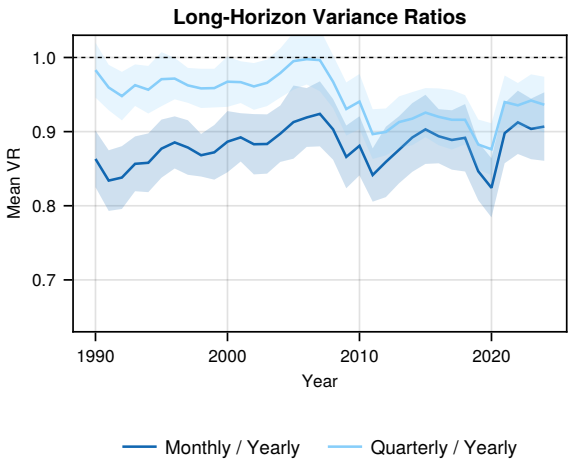
[20] Our results also hold when we residualize returns in the time series against the factors directly. We favor the cross-sectional approach as it only uses information available at the time of the return.

Figure 11: **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 (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



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.

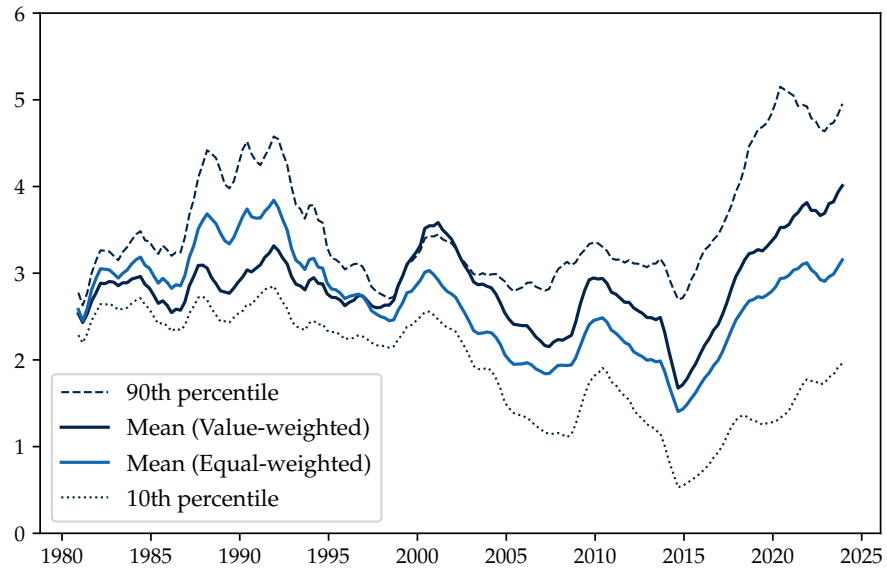
3.8 Structural Evidence

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.[21] The diagonal elements of the aggregate coliquidity matrix measure the long-term price impact of persistent demand shifts. Figure 12 plots the cross-sectional distribution of long-term impact over time.

Figure 12: **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 12 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 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.

[21] 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.

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.

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

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 3 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 3: **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

	Quarterly Returns				
	(1)	(2)	(3)	(4)	(5)
FIT	3.006***			1.792**	
	(0.498)			(0.598)	
gross FIT		0.861***		0.075	0.158
		(0.109)		(0.158)	(0.151)
net FIT			0.542***	0.269**	0.458***
			(0.062)	(0.096)	(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

	Quarterly Returns				
	(1)	(2)	(3)	(4)	(5)
DIT	11.421***			5.860***	
	(1.433)			(1.255)	
gross DIT		1.543***		0.336	0.619**
		(0.222)		(0.195)	(0.190)
net DIT			1.592***	1.043***	1.253***
			(0.200)	(0.170)	(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. Volume measures are expressed as fractions of shares outstanding and all explanatory variables are cross-sectionally standardized. Table 4 reports the results.

Table 4: **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. The 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. All explanatory variables are standardized cross-sectionally.

	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)
Stock	-	x	-	x	-	x	-	x
Day	x	-	x	x	x	-	x	x
Observations	8024758	8024753	8024758	8024753	8024758	8024753	8024758	8024753
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 4 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. First, as discussed above, net volume may more accurately reflect long-term liquidity, understood as the markets 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 5 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 the net-volume quintiles, the return spread between high and low gross volume stocks is largely insignificant and has the wrong sign. In contrast, sorting first on gross volume and then on net volume results in return spreads that are negative and statistically significant for all quintiles. These findings are further confirmed in Fama-MacBeth regressions of four-factor adjusted returns onto both gross and net volume. Panel (b) of Table 5 shows that across different sets of controls, net volume significantly predicts returns.

Table 5: **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, and market equity. 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
	(-0.64)		(-0.25)		(0.25)	(0.42)
net Vol.		-0.925***		-0.688**	-0.961***	-0.778***
		(-3.27)		(-2.45)	(-3.75)	(-3.25)
ln(Mcap)			-0.181***	-0.163***		-0.167***
			(-4.95)	(-5.00)		(-4.75)
Adj. R^2	0.006	0.002	0.009	0.005	0.008	0.011
Avg. Obs	1872	1853	1872	1853	1853	1853

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.3. 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 markets 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.[22] 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, 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

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

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.[23] 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.

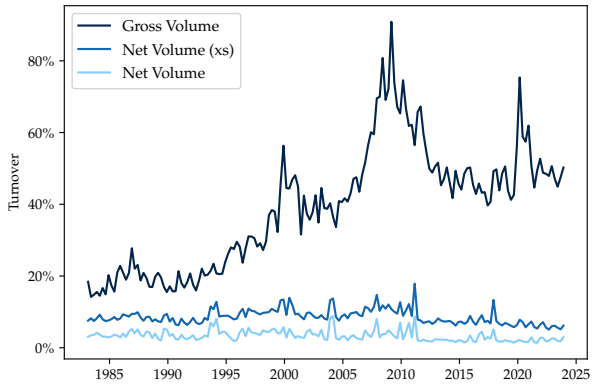
5.3 The Evolution of Market Level Net Volume

Panel (a) of Figure 13 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 13 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, indicating that cross-sectional round-trip trading has not materially changed over time.

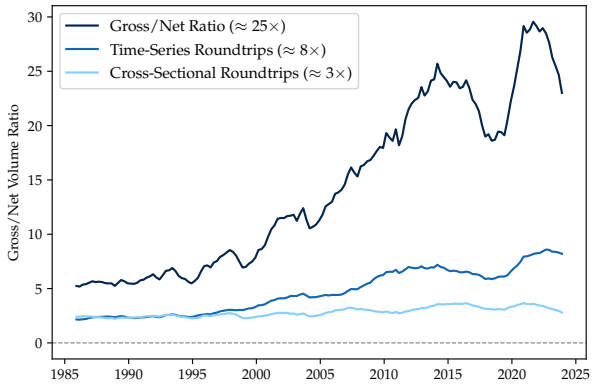
[23] The denominator in (9) is total stock market equity, given by $\sum_n P_t(n) \cdot \text{Shrout}_t(n)$.

Figure 13: **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), we argue that *net* trading volume rather than gross volume is the economically relevant object at longer horizons. The large wedge between gross and net volume for the aggregate stock market sheds useful light on the findings of Gabaix and Koijen (2021), who document that the aggregate stock market is quite inelastic: flows in and out of the stock market have a relatively large impact on prices. They estimate a multiplier of approximately 5, meaning that buying 1% of the aggregate stock market leads to a 5% increase in aggregate equity market capitalization. This multiplier may seem strikingly large at first glance, but it becomes less surprising once one recognizes how low net volume at the market level is. With net volume of only about 2.5% of market capitalization per quarter, purchasing 1% of the stock market amounts to absorbing nearly half of all net trading activity in that quarter. Viewed through this lens, the large price impact documented by Gabaix and Koijen (2021) is not a puzzle but a natural consequence of the limited capacity of the market to absorb net demand shifts underscoring the economic importance of the distinction between gross and net volume.

The distinction between gross and net volume also has implications for aggregate return predictability. Jones (2002) documents that equity turnover negatively predicts market excess returns, interpreting this as a liquidity premium. We revisit this evidence in Appendix Section B.2 and show that gross volume has lost its predictive power, while net volume strongly predicts market excess

returns across all horizons with adjusted R^2 reaching 12% at the five-year horizon. Whether this predictability reflects a liquidity premium or sentiment-driven demand pressure in the spirit of Baker and Stein (2004), it reinforces our central point: net volume, not gross volume, is the economically relevant object for understanding longer-horizon market dynamics. We defer the full analysis to the Appendix, as our paper's main focus lies in showing the unchanged long-term liquidity at the stock level, but we believe these aggregate results offer a promising avenue for future work.

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, long-term reversal 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 long horizons. 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.

An intriguing question is why quarterly net volume also matters for liquidity at very high frequencies. We conjecture that 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. Finally, while high-frequency trading cannot *directly* provide long-term liquidity to persistent demand shifts, it may do so *indirectly* by attracting more elastic long-horizon investors who would otherwise avoid poorly intermediated stocks due to the high cost of occasional urgent trades, such as those triggered by unexpected flows or portfolio rebalancing. Exploring these mechanisms is an important avenue for future research.

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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, $f^u_{j,t}$ measures the unexpected part of the flow given the fund's past.

In addition, we also calculate so-called flow shocks, $f^{shock}_{i,t}$. 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 $FIT^u_t(n)$ and $FIT^{shock}_t(n)$ according to equation (A.1).

A.2 Variance Ratio Methodology

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 the sampe mean $\hat{\mu} = \frac{1}{T}\sum_{t=1}^T r_t$, one-period variance $\hat{\sigma}_1^2 = \frac{1}{T-1}\sum_{t=1}^T (r_t - \hat{\mu})^2$ and the k-period overlapping variance $\hat{\sigma}_k^2 = \frac{1}{m}\sum_{t=k}^T \left(r_t^{(k)} - k\hat{\mu}\right)^2$ where $r_t^{(k)} = \sum_{j=0}^{k-1} r_{t-j}$ is the k-period return ending at t, and $m = k(T-k+1)\left(1-\frac{k}{T}\right)$ is a bias-correction factor that accounts for the reduced degrees of freedom from overlapping observations. The variance ratio is then:

$$VR(k) = \frac{\hat{\sigma}_k^2}{\hat{\sigma}_1^2}. \tag{A.3}$$

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.

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

$$r_t(n) = \sum_j \beta_{j,t} X_{j,t-1}(n) + \text{Ind.FE}_t(n) + \varepsilon_t(n), \tag{A.4}$$

where $r_t(n)$ is the return for stock n, $X_{j,t-1}(n)$ are lagged characteristics, $\text{Ind.FE}_t(n)$ 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

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. 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. 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.3 Constructing Net Amihud versus Gross Amihud

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

$$\text{Gross Amihud}_{nt} = \frac{1}{D_{nt}} \sum_{d=1}^{D_{nt}} \frac{|r_{nd}|}{\text{Gross Volume}_{nd}}, \tag{A.5}$$

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

$$\text{Net Amihud}_{nt} = \frac{1}{D_{nt}} \sum_{d=1}^{D_{nt}} \frac{|r_{nd}|}{\text{Net Volume}_{nd}}, \tag{A.6}$$

where Net Volume_{nd} is the net volume on day d in month t.[24]

Appendix B Additional Empirical Results

B.1 The Frequency of Roundtrip Trades: Evidence from Variance Ratios

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 the frequency of roundtrip trades. 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.

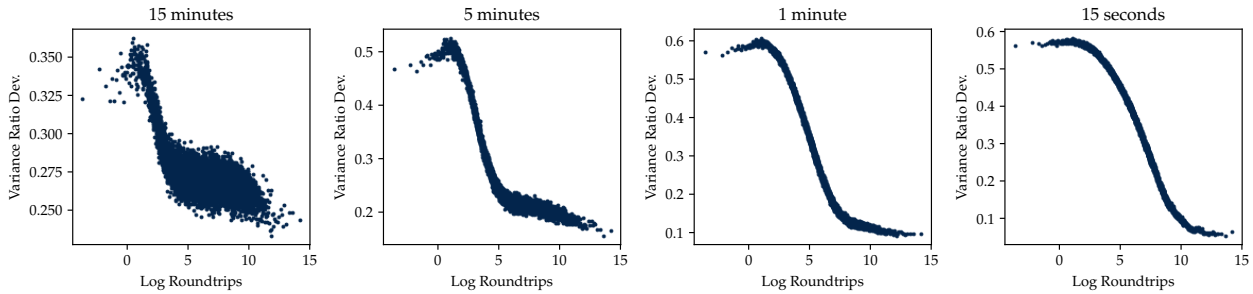
$$\text{Round-trips}_t(n) = \ln(\text{Gross Dollar Volume}_t(n) - \text{Net Dollar Volume}_t(n)), \tag{B.1}$$

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.[25] We then test whether round-trip trading is related to these variance ratio deviations, and at which frequencies. Figure B.1 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.

[24] 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).

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

Figure B.1: **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 $\left|\frac{\text{Var}(r_{k,t}(n))}{k \cdot \text{Var}(r_t(n))} - 1\right|$. 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.



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. Table B.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%.[26] 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.

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

Table B.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)	(8)
Variance Ratio Dev. (15 seconds)	-9.696***						-7.201***	-2.087***
	(0.082)						(0.090)	(0.041)
Variance Ratio Dev. (1 min)		-7.630***					-2.929***	-1.219***
		(0.077)					(0.044)	(0.025)
Variance Ratio Dev. (5 min)			-3.216***				-0.860***	-0.346***
			(0.082)				(0.022)	(0.012)
Variance Ratio Dev. (15 min)				-0.515***			-0.181***	-0.066***
				(0.026)			(0.007)	(0.003)
Variance Ratio Dev. (30 min)					0.142***		0.028***	0.013***
					(0.011)		(0.004)	(0.002)
Variance Ratio Dev. (1 day)						-1.417***	-0.359***	-0.176***
						(0.056)	(0.018)	(0.012)
Day	x	x	x	x	x	x	x	x
Stock	-	-	-	-	-	-	-	x
Observations	8953089	8953089	8953089	8953089	8953089	8953089	8953089	8953089
R^2	0.648	0.512	0.129	0.048	0.046	0.058	0.699	0.875
R^2 Within	0.631	0.489	0.087	0.003	0.000	0.013	0.684	0.142

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

B.2 Market-Level Net Volume and Return Predictability

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.[27] We revisit and run predictive regressions of market excess returns on market level gross and net volume over various return horizons.[28]

Table B.2 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.[29] More importantly, however, net volume predicts future returns across all horizons. These findings are also confirmed in multivariate

[27] 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*.

[28] 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 month minus the one-month Treasury bill rate.

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

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 B.2: **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.[30] 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 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.

[30] 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.

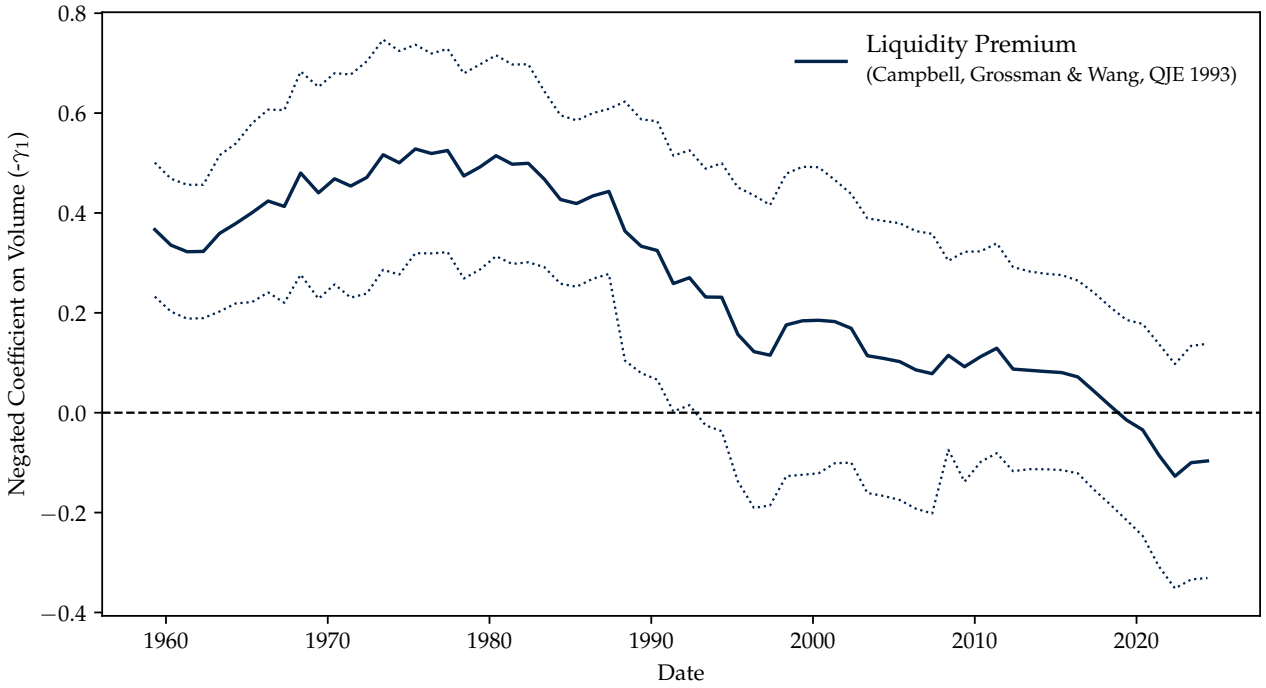
B.3 Daily Price Impact: Evidence from the Aggregate Stock Market

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

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

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.2) using a rolling 20-year window regressions. Figure B.2 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).

Figure B.2: **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.4 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.3 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.1 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.3: **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).

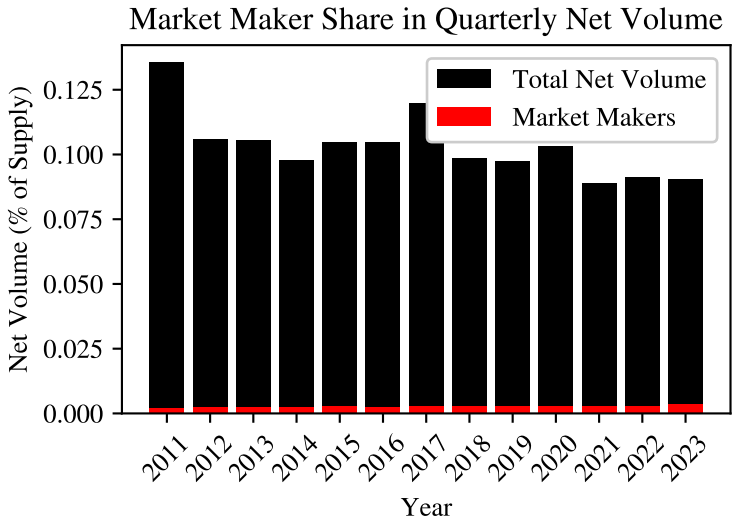


Figure C.2: **Price Impact from Flow-Shocks over Time**
The figure plots the estimated coefficients from 10-year rolling windows regressions of quarterly returns onto quarterly flow-shock induced trades. Flow shocks are calculated by removing the cross-sectional average flow on any given date from raw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

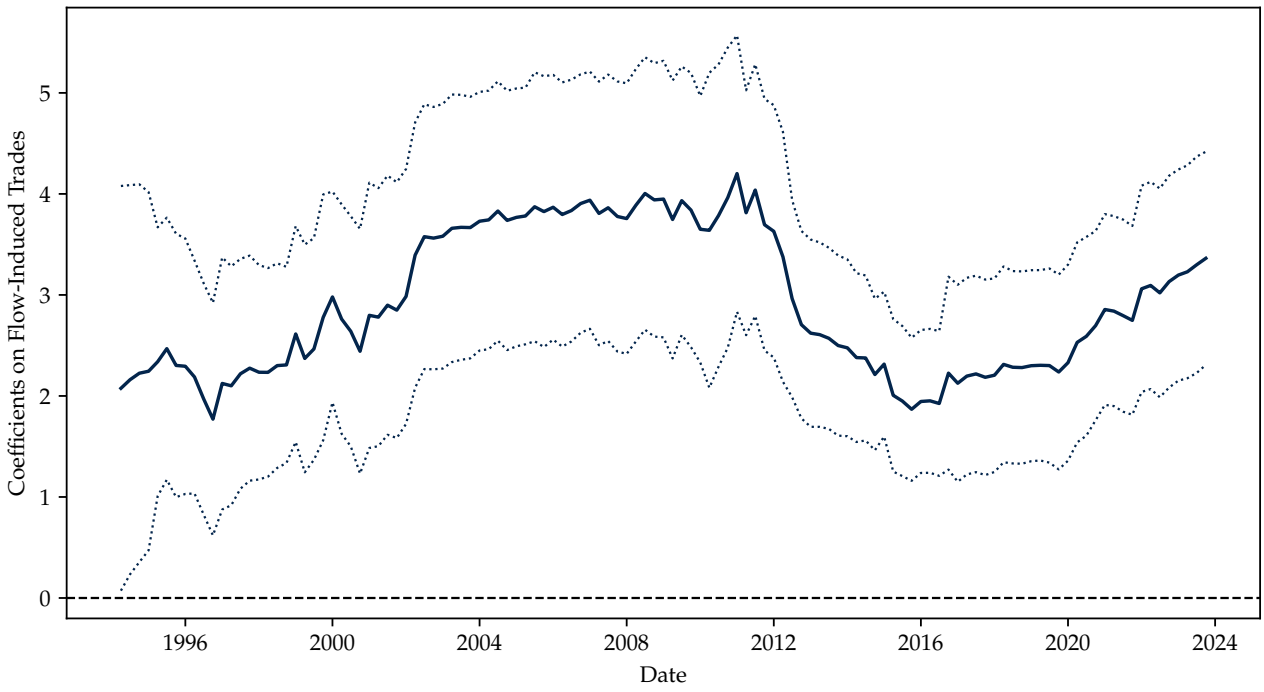


Figure C.3: **Price Impact from Unexpected Flows over Time**
The figure plots the estimated coefficients from 10-year rolling windows regressions of quarterly returns onto quarterly unexpected flow induced trades. Unexpected flows are defined as the residuals from regressing fund flows on its own lagged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

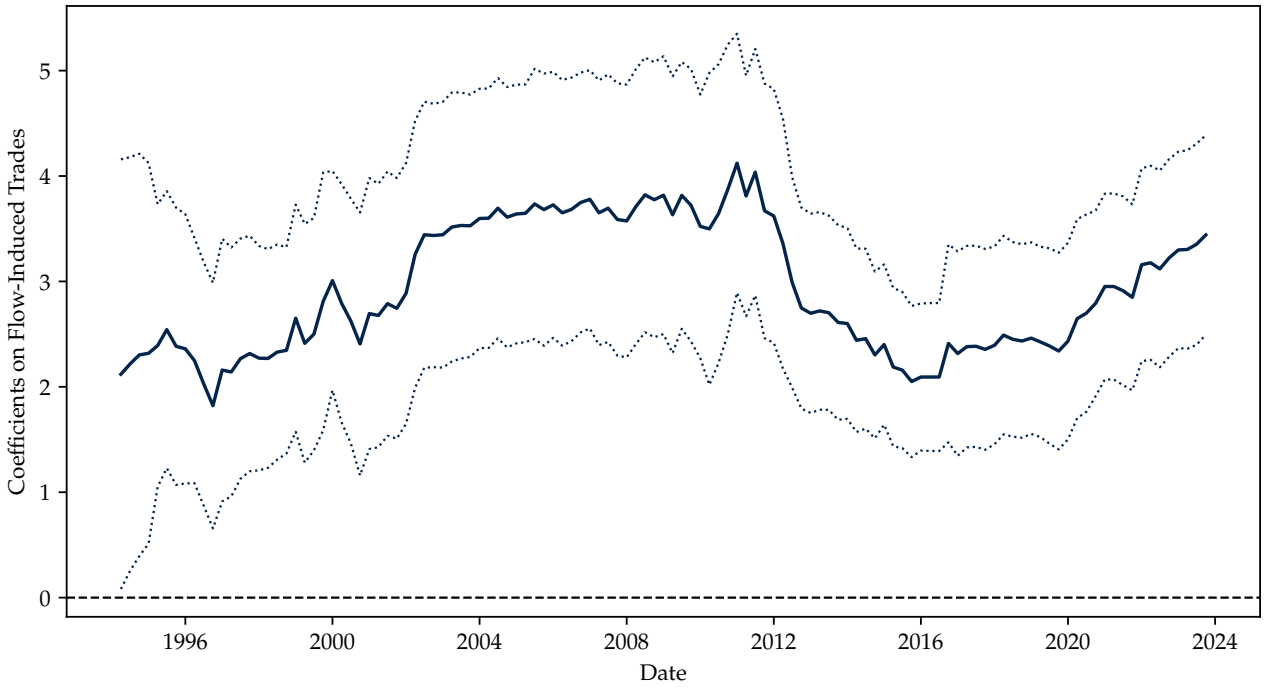


Figure C.4: **Decline of High Frequency Reversal: FMB Regressions**
The figure plots the coefficient obtained from daily Fama-MacBeth regressions of returns onto past three-day cumulative returns, controlling for market beta and lagged (log) market equity. We plot the 10-year rolling average of the coefficient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

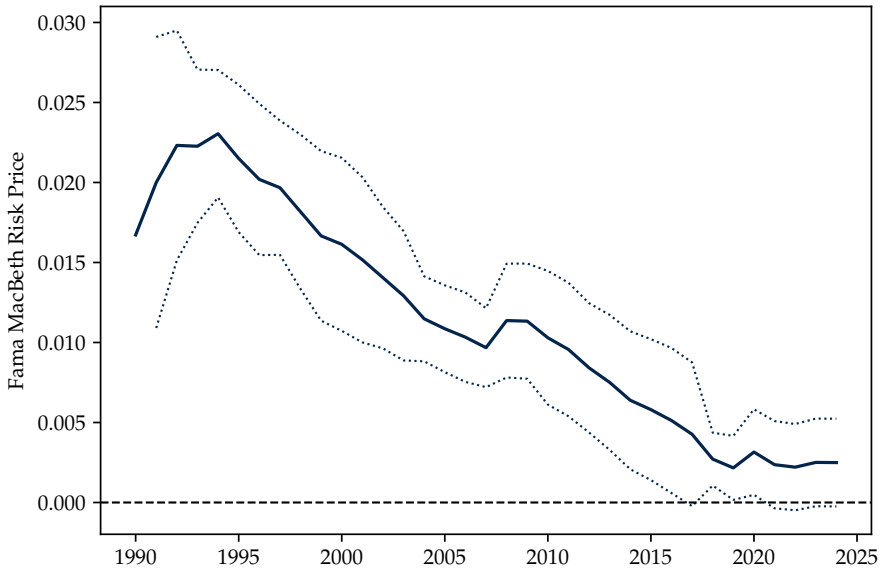
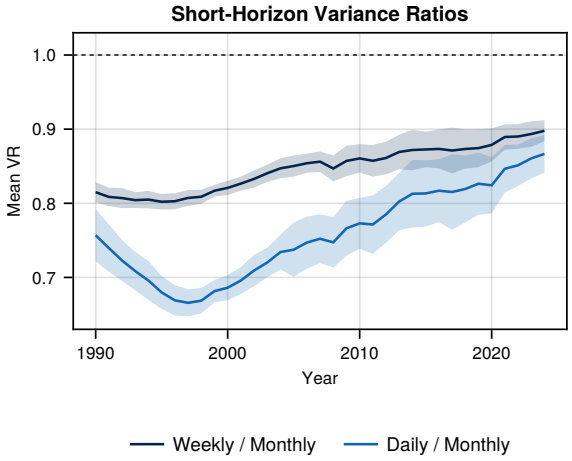


Figure C.5: **Variance Ratios Over Time: Momentum and Reversal Controls**
The figure replicates Figure 11 with abnormal returns additionally residualized against momentum, short-term reversal, and long-term reversal characteristics. Panel (a) shows short-horizon variance ratios (daily-to-monthly and weekly-to-monthly). Panel (b) shows long-horizon variance ratios (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

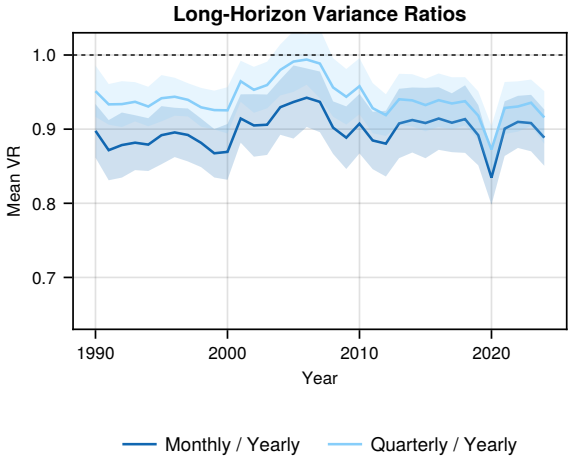


Table C.1: **Long-Term Impact: Time Trends**
The table reports results from regressing quarterly returns onto dividend-induced trades, controlling for the dividend payout ratio. The variables $D(\cdot)$ indicate decade dummies. period is from 1980:Q1 to 2023:Q4. The reported standard errors in parentheses are clustered by date.

	Quarterly Returns			
	(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.2: **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.

	Quarterly Returns		
	(1)	(2)	(3)
FIT	3.006***	3.018***	
	(0.498)	(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.3: **Flow-Induced Impact: Reversal**

The table reports results from pooled regressions of quarterly returns onto flow-induced trades. The sample period is from 1980:Q1 to 2023:Q4. (1) and (2) are regressions of returns onto different lags of flow-induced trades. (3)-(6) are regressions of future cumulative returns onto contemporaneous flow-induced trades. The reported standard errors in parentheses are clustered by date.

	Return_t		$\text{Future Return}_{t+1}$	$\text{Future Return}_{t+2}$	$\text{Future Return}_{t+3}$	$\text{Future Return}_{t+4}$
	(1)	(2)	(3)	(4)	(5)	(6)
FIT_t	4.427***	4.342***	-0.124	-0.943	-1.914	-2.797
	(0.328)	(0.344)	(0.340)	(0.588)	(1.066)	(1.441)
FIT_{t-1}	-1.168***					
	(0.339)					
FIT_{t-2}	-0.838*					
	(0.402)					
FIT_{t-3}	-0.813					
	(0.629)					
FIT_{t-4}	-0.618					
	(0.496)					
$\overline{FIT}_{t-4}$		-3.387***				
		(0.731)				
Date	x	x	x	x	x	x
Observations	347412	347412	411966	398645	385690	373148
R^2	0.187	0.187	0.172	0.168	0.170	0.168
R^2 Within	0.005	0.004	0.000	0.000	0.000	0.000

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	347825	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)
$\frac{FIT}{\text{Shrout.}}$	3.472***				2.571***
	(0.493)				(0.507)
$\frac{FIT}{\text{Gross Vol.}}$		0.175***			-0.270***
		(0.042)			(0.062)
$\sqrt{\frac{FIT}{\text{Gross Vol.}}}$			0.108***		-0.032
			(0.020)		(0.065)
$\sigma\sqrt{\frac{FIT}{\text{Gross Vol.}}}$				0.562***	0.675**
				(0.084)	(0.238)
Date	x	x	x	x	x
Observations	197420	197420	197420	190278	190278
R^2	0.145	0.144	0.145	0.150	0.150
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)
$\frac{FIT}{\text{Shrout.}}$	3.445***				2.931***
	(0.400)				(0.408)
$\frac{FIT}{\text{Gross Vol.}}$		0.281***			-0.225***
		(0.074)			(0.064)
$\sqrt{\frac{FIT}{\text{Gross Vol.}}}$			0.124***		-0.022
			(0.023)		(0.065)
$\sigma\sqrt{\frac{FIT}{\text{Gross Vol.}}}$				0.592***	0.431
				(0.086)	(0.256)
Date	x	x	x	x	x
Observations	214678	214678	214678	208895	208895
R^2	0.207	0.205	0.206	0.210	0.211
R^2 Within	0.003	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.

(a) Net volume then gross volume: α_{FF4}^{EW} (%)

	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_{FF4}^{EW} (%)

	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***

(b) 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	\$19.53	47%
Net Volume (xs)	\$2.12	5%
Net Volume	\$0.75	2%

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
Log Roundtrips (Dollars)	mean	8.475	8.832	9.082	9.469
	median	8.424	8.740	8.985	9.318
	IQR	1.463	1.138	1.052	1.203
	stdev	1.135	0.931	0.886	0.988
Variance Ratio (15 seconds)	mean	0.153	0.137	0.162	0.151
	median	0.128	0.116	0.140	0.120
	IQR	0.160	0.142	0.182	0.181
	stdev	0.119	0.103	0.118	0.119
Variance Ratio (1 min)	mean	0.142	0.128	0.122	0.110
	median	0.112	0.103	0.098	0.089
	IQR	0.146	0.131	0.125	0.113
	stdev	0.123	0.106	0.101	0.090
Variance Ratio (5 min)	mean	0.219	0.209	0.205	0.193
	median	0.180	0.173	0.171	0.161
	IQR	0.223	0.212	0.210	0.197
	stdev	0.176	0.167	0.162	0.154
Variance Ratio (15 min)	mean	0.265	0.267	0.267	0.264
	median	0.228	0.230	0.229	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	0.290	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	0.206	0.207	0.208
Variance Ratio (1 day)	mean	0.238	0.213	0.230	0.221
	median	0.217	0.193	0.205	0.197
	IQR	0.239	0.213	0.230	0.228
	stdev	0.162	0.149	0.161	0.156

(b) Small Cap Stocks

		2005	2010	2015	2020
Log Roundtrips (Dollars)	mean	3.512	3.387	3.852	4.122
	median	3.599	3.395	3.910	4.236
	IQR	1.760	1.539	1.931	1.896
	stdev	1.347	1.241	1.438	1.431
Variance Ratio (15 seconds)	mean	0.519	0.524	0.501	0.505
	median	0.527	0.530	0.509	0.517
	IQR	0.119	0.125	0.125	0.127
	stdev	0.098	0.100	0.104	0.108
Variance Ratio (1 min)	mean	0.461	0.483	0.451	0.461
	median	0.481	0.500	0.465	0.485
	IQR	0.232	0.221	0.234	0.245
	stdev	0.170	0.163	0.169	0.178
Variance Ratio (5 min)	mean	0.329	0.354	0.336	0.357
	median	0.310	0.344	0.311	0.332
	IQR	0.326	0.327	0.339	0.379
	stdev	0.211	0.211	0.218	0.230
Variance Ratio (15 min)	mean	0.290	0.283	0.288	0.301
	median	0.251	0.245	0.248	0.266
	IQR	0.302	0.296	0.303	0.312
	stdev	0.212	0.206	0.213	0.212
Variance Ratio (30 min)	mean	0.298	0.287	0.284	0.285
	median	0.257	0.246	0.239	0.243
	IQR	0.319	0.309	0.314	0.315
	stdev	0.215	0.211	0.214	0.213
Variance Ratio (1 day)	mean	0.275	0.267	0.258	0.262
	median	0.250	0.242	0.229	0.236
	IQR	0.273	0.271	0.259	0.262
	stdev	0.189	0.187	0.186	0.182