

7524755-how-small-trade-measures-reverse-liquidity-inference-a-value-count-decomposition

SUMMARY: This paper examines how small-trade measures affect liquidity inference in Chinese A-share stocks. The authors derive an exact value-count decomposition that separates relative small-trade frequency, relative trade size, total transaction count, and average trade value. Using weekly panel data for Chinese A-share stocks, they reject the equal-loading restrictions imposed by aggregated value measures. They find that an innovation in small-trade value composition is associated with a 0.612-basis-point narrower quoted spread on impact. When both execution composition and aggregate trading scale are decomposed, the count-composition coefficient becomes positive at 0.278 basis points per marginal standard deviation. The positive association is concentrated near impact and attenuates over the following two weeks, becoming statistically indistinguishable from zero at the one-year horizon. The results suggest that liquidity inference can reverse when value-based trading measures aggregate underlying margins with unequal spread associations.

METHOD: The study uses weekly data for Shanghai and Shenzhen A-share stocks from December 2015 to December 2025. The authors derive an exact value-count decomposition of small-trade value composition into small-trade count composition and relative average trade size, and a decomposition of total trading value into total transaction count and average trade value. They project each margin on the same 52-week history of all four states, predetermined controls, and stock and week fixed effects. They then compare nested measurement models and estimate horizon-specific spread associations on an identical common sample.

KEY FINDINGS:

- An innovation in the unseparated small-trade value-composition measure is associated with a 0.612-basis-point narrower quoted spread on impact.
- When both execution composition and aggregate trading scale are decomposed, the count-composition coefficient becomes positive at 0.278 basis points per marginal standard deviation.
- The positive association is concentrated near impact and attenuates over the following two weeks.
- The joint restriction is rejected at every reported horizon.

IMPLICATION FOR TRADING: The findings suggest that liquidity inference can reverse when value-based trading measures aggregate underlying margins with unequal spread associations. Practitioners should be cautious when using aggregated value measures to infer liquidity, as they may not accurately reflect the true composition of small trades. This research highlights the importance of separating small-trade frequency, relative trade size, and aggregate trading scale to better understand and predict liquidity.

How Small-Trade Measures Reverse Liquidity Inference:A Value--Count Decomposition

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Abstract

Small-trade value shares are widely used to characterize retail participation and fragmented execution, but they combine economically distinct dimensions of trading activity. We derive an exact value–count decomposition that separates relative small-trade frequency, relative trade size, total transaction count, and average trade value. Under a common first-stage projection, regressions using aggregated value measures impose equal-loading restrictions across these margins. Using a weekly panel of Chinese A-share stocks, we strongly reject these restrictions on an identical estimation sample. An innovation in unseparated small-trade value composition is associated with a 0.612-basis-point narrower quoted spread on impact. After separating both execution composition and aggregate trading scale, the count-composition coefficient is instead positive at 0.278 basis points per marginal standard deviation, or 0.103 basis points per conditional standard deviation. The positive association is concentrated near impact, attenuates sharply over the following two weeks, and is statistically indistinguishable from zero at the one-year horizon. Split-week evidence locates the reversal in early-week quote formation without showing clean subsequent propagation. The results show that liquidity inference can reverse when value-based trading measures aggregate underlying margins with unequal spread associations.

Keywords: small trades; trade-size composition; transaction frequency; bid–ask spreads; local projections; market microstructure

1 Introduction

Small trades are among the most visible features of electronic markets and among the most difficult to interpret. A high small-trade share is often viewed as evidence of retail participation, order splitting, or fragmented execution. Yet transaction size does not identify either the trader or the underlying parent order. A household may submit a small order directly, an institution may divide a large order into many small executions, and the number of small trades may rise simply because trading in the stock becomes unusually active. These cases need not have the same implications for information, inventory, or liquidity.

The problem is not only one of trader classification. It also arises from the way value-based trading measures aggregate distinct margins. A larger fraction of value executed through small trades can reflect either more small trades relative to non-small trades or a change in their relative average size. Separately, total trading value can change because total transaction count or average trade value changes. These margins are linked by accounting identities, but they represent distinct economic objects. Relative transaction frequency describes how executions are distributed across size categories. Relative trade size describes the average value transferred by a small trade relative to a non-small

trade. Total transaction count and average trade value describe the scale of trading activity. A specification using small-trade value composition together with total trading value therefore compresses four underlying margins into two regressors.

This paper asks whether that aggregation changes liquidity inference. We first derive an exact decomposition of small-trade value composition into small-trade count composition and relative average trade size. A second exact identity decomposes total trading value into total transaction count and average trade value. When all components are projected on the same information set, these identities continue to hold for the resulting residuals. A regression using the two aggregated value measures therefore imposes two equal-loading restrictions: quoted spreads must load equally on relative transaction frequency and relative trade size, and equally on total transaction count and average trade value. These restrictions arise from the construction of the measures rather than from market-microstructure theory.

We test these restrictions using weekly data for Shanghai and Shenzhen A-share stocks. This setting is informative because substantial household participation coexists with institutional execution, while CSMAR applies a stable nominal classification to trades below RMB 50,000. We combine transaction values and counts, quoted spreads, prices, and firm characteristics through December 2025. To construct the four execution-margin innovations, we project each margin on the same 52-week history of all four states, predetermined controls, and stock and week fixed effects. We then compare nested measurement models and estimate horizon-specific spread associations on an identical common sample.

The main finding is a sign reversal under an otherwise unchanged empirical design. On the same 1,437,390 stock-weeks, an innovation in the unseparated small-trade value-composition measure is associated with a 0.612-basis-point narrower spread on impact. Decomposing value composition alone leaves the small-trade frequency coefficient negative. Once both composition and activity scale are decomposed, however, the coefficient turns positive, reaching 0.278 basis points per marginal standard deviation. Both equal-loading restrictions are rejected, and the joint restriction is rejected at every reported horizon. Because innovations in small-trade frequency and average trade value are highly correlated, scaling by the conditional standard deviation yields a more conservative estimate of 0.103 basis points. The economic importance of the result lies less in the standalone magnitude than in the fact that aggregation assigns the opposite sign to the frequency margin.

The dynamic evidence qualifies rather than strengthens the impact result. The positive unrestricted coefficient falls by roughly half after one week and declines further after two weeks. Later weekly coefficients largely inherit the spread state established near impact, and split-week estimates locate the reversal in early-week quote formation without showing clean propagation into the late-week spread. The result is also present across predetermined price groups, making a purely mechanical explanation based on the nominal trade-size cutoff difficult to sustain. We therefore

interpret the estimates as a conditional coefficient path rather than as a structurally identified liquidity response.

The paper contributes to several related literatures through a single measurement result. Research on trading activity has long distinguished transaction frequency from trade size (Jones et al., 1994; Lin et al., 1995; Chan and Fong, 2000; Huang and Masulis, 2003). Small trades are often used as proxies for retail participation (Hvidkjaer, 2008; Boehmer et al., 2021), but trade size does not uniquely identify trader type. Institutional orders may be executed through sequences of child orders (Keim and Madhavan, 1995; van Kervel and Menkveld, 2019), and small or odd-lot executions can also carry information (O'Hara et al., 2014; Lei et al., 2026). We therefore do not claim that counts and sizes have newly discovered economic content. Our contribution is to derive the exact restrictions imposed when a fixed-threshold value share recombines these margins, test those restrictions under a common residual-maker and sample, and show that they can reverse liquidity inference. The lesson extends beyond the Chinese setting: whenever a transaction-category value share is used together with an aggregate-value measure, the resulting specification can conceal unequal loadings on relative transaction frequency, relative average size, total transaction count, and average transaction value.

The remainder of the paper is organized as follows. Section 2 develops the measurement framework and relates it to the existing literature. Section 3 describes the institutional setting, data, and variable construction. Section 4 presents the empirical design. Section 5 reports the main measurement results and examines their timing and sensitivity to the nominal trade-size threshold. Section 6 evaluates robustness and stability. Section 7 discusses interpretation and broader implications. Section 8 concludes.

2 Measurement framework and testable restrictions

This section converts the measurement problem into testable regression restrictions. We first distinguish value composition from count composition and derive an exact decomposition of the two. We then separate total trading value into total transaction count and average trade value. Finally, we show that the two aggregated value measures impose pairwise equality restrictions on the coefficients of the four underlying margins.

2.1 Small-trade value shares as compositional measures

Let $V_{i,w}^S$ and $V_{i,w}^N$ denote the value executed through small and non-small trades for stock i in week w , and let $N_{i,w}^S$ and $N_{i,w}^N$ denote the corresponding transaction counts. The corresponding value and count shares are

$$s_{i,w}^S = \frac{V_{i,w}^S}{V_{i,w}^S + V_{i,w}^N}, \quad s_{i,w}^N = \frac{N_{i,w}^S}{N_{i,w}^S + N_{i,w}^N} \quad \#(1)$$

The two shares describe different aspects of trading activity. The value share measures how trading value is distributed across trade-size categories, whereas the count share measures how transaction

frequency is distributed. The same value share can arise from many relatively small executions or from fewer relatively large ones. By itself, the value share therefore does not distinguish relative transaction frequency from relative trade size.

Because each small-trade component is defined relative to its non-small counterpart, we represent the resulting two-part compositions using orthonormal log-ratio coordinates (Aitchison, 1982; Egozcue et al., 2003):

$$x_{i,w}^{VC} = \frac{1}{\sqrt{2}} \log \left(\frac{V_{i,w}^S}{V_{i,w}^N} \right), \quad x_{i,w}^{NC} = \frac{1}{\sqrt{2}} \log \left(\frac{N_{i,w}^S}{N_{i,w}^N} \right) \quad \#(2)$$

The factor $1/\sqrt{2}$ normalizes the contrast between the two components. For positive components, each log-ratio coordinate is a one-to-one transformation of its corresponding raw share, so the transformation changes the coordinate system without discarding information. It also places the composition on an unconstrained scale and makes the decomposition below additive.

2.2 An exact value–count decomposition

Within each trade-size category, executed value equals transaction count times average trade value. This relation yields two exact decompositions. First, value composition can be written as

$$x_{i,w}^{VC} = x_{i,w}^{NC} + x_{i,w}^{RS} \quad \#(3)$$

where

$$x_{i,w}^{RS} = \frac{1}{\sqrt{2}} \log \left(\frac{V_{i,w}^S/N_{i,w}^S}{V_{i,w}^N/N_{i,w}^N} \right) \quad \#(4)$$

The coordinate $x_{i,w}^{RS}$ is the normalized log ratio of average small-trade value to average non-small-trade value. Equation (3) therefore separates value composition into relative transaction frequency and relative average trade size.

A second identity separates activity scale. Total trading value satisfies

$$\underbrace{\log(V_{i,w}^S + V_{i,w}^N)}_{x_{i,w}^{TV}} = \underbrace{\log(N_{i,w}^S + N_{i,w}^N)}_{x_{i,w}^{TC}} + \underbrace{\log\left(\frac{V_{i,w}^S + V_{i,w}^N}{N_{i,w}^S + N_{i,w}^N}\right)}_{x_{i,w}^{AV}} \quad \#(5)$$

Thus, log total trading value is the sum of log total transaction count and log average value per transaction.

We collect the four underlying margins in the state vector

$$X_{i,w} = (x_{i,w}^{NC}, x_{i,w}^{RS}, x_{i,w}^{TC}, x_{i,w}^{AV})'$$

The first two coordinates describe the relative composition of execution across trade-size categories: x^{NC} captures relative transaction frequency and x^{RS} captures relative average trade size. The last two describe the overall scale of trading activity through transaction count and average value per transaction. This construction combines standard compositional coordinates with the established distinction between transaction frequency and average trade size (Jones et al., 1994; Chan and Fong, 2000; Huang and Masulis, 2003). Its empirical content arises when the four underlying margins are

recombined into value composition and total trading value, thereby imposing restrictions on their regression coefficients.

2.3 Aggregation and equal-loading restrictions

Let $\mathcal{M}$ denote a common linear residual-maker and $u^q = \mathcal{M}x^q$ denote the residualized coordinate q . Applying the same operator to equations (3) and (5) preserves both identities:

$$u^{VC} = u^{NC} + u^{RS}, \quad u^{TV} = u^{TC} + u^{AV} \quad \#(6)$$

Using a common projection is essential. The residual identities would generally fail if the components were projected on different histories, controls, or samples.

Consider an aggregated specification that includes only the value-composition and total-value innovations. Let $W_{i,w-1}$ collect the predetermined controls and spread history held fixed across the nested specifications:

$$\text{Spread}_{i,w+h} = \alpha_i^h + \lambda_w^h + \tilde{\beta}_h^{VC} u_{i,w}^{VC} + \tilde{\beta}_h^{TV} u_{i,w}^{TV} + W'_{i,w-1} \Pi_h + \varepsilon_{i,w+h} \quad \#(7)$$

Substituting equation (6) into equation (7) yields

$$\begin{aligned} \text{Spread}_{i,w+h} = & \alpha_i^h + \lambda_w^h + \tilde{\beta}_h^{VC} u_{i,w}^{NC} + \tilde{\beta}_h^{VC} u_{i,w}^{RS} \\ & + \tilde{\beta}_h^{TV} u_{i,w}^{TC} + \tilde{\beta}_h^{TV} u_{i,w}^{AV} + W'_{i,w-1} \Pi_h + \varepsilon_{i,w+h} \end{aligned} \quad \#(8)$$

Comparing equation (8) with an unrestricted four-state regression shows that the coarse model imposes

$$\beta_h^{NC} = \beta_h^{RS} = \tilde{\beta}_h^{VC}, \quad \beta_h^{TC} = \beta_h^{AV} = \tilde{\beta}_h^{TV} \quad \#(9)$$

The first equality requires the spread to load identically on relative transaction frequency and relative trade size. The second requires identical loadings on total transaction count and average trade value. These are testable restrictions imposed by the use of the aggregated regressors.

Neither equality in equation (9) is implied by market-microstructure theory. The four underlying margins describe different dimensions of execution and may therefore have different associations with quoted liquidity. Whether the equal-loading restrictions hold is an empirical question. The next subsection relates these margins to the existing literature and clarifies the paper's measurement contribution.

2.4 Relation to existing research

The measurement framework builds on the longstanding distinction between transaction frequency and trade size. Research on trading activity shows that the number and size of transactions can have different associations with volatility, spreads, order imbalance, market depth, and aggregate liquidity conditions (Jones et al., 1994; Lin et al., 1995; Chan and Fong, 2000; Chordia et al., 2001; Huang and Masulis, 2003). We do not claim that this distinction is new. Our question is different: what restrictions are imposed when a fixed-threshold value measure recombines frequency and size, and when total trading value similarly recombines transaction count and average trade value? Equations (3)–(9) make those restrictions explicit.

A related literature shows why transaction size can contain information without uniquely identifying trader identity. Informed traders may choose trade size strategically, so market makers can condition prices on the size as well as the sequence of trades (Easley and O'Hara, 1987). More generally, observed trade size is an endogenous execution choice: traders may divide or concentrate orders in response to information, urgency, market depth, execution costs, and concealment (Kyle, 1985; Barclay and Warner, 1993; Keim and Madhavan, 1995; Chan and Lakonishok, 1995; Chakravarty, 2001). Institutional parent orders can therefore appear as sequences of small executions (van Kervel and Menkveld, 2019), and economically important information can reside in trades conventionally classified as small (O'Hara et al., 2014). At the same time, empirical studies use trade size, execution location, and price improvement to construct empirically useful, though imperfect, proxies for retail activity (Lee and Radhakrishna, 2000; Hvidkjaer, 2008; Barber et al., 2009; Boehmer et al., 2021). Direct validation of the Boehmer et al. classification documents material variation in identification and signing accuracy across stocks, reinforcing the distinction between a useful transaction-based proxy and trader identity (Barber et al., 2024). These approaches need not be inconsistent. Trade size can be informative about investor participation without providing a one-to-one mapping from an observed execution to an underlying account or parent order. Even when retail participation is observed more directly, its liquidity implications need not be one-directional: retail investors can supply liquidity in some settings, whereas participation by less sophisticated retail traders can reduce market quality in others (Barrot et al., 2016; Eaton et al., 2022).

This distinction matters for liquidity because the four margins in our decomposition can represent different economic forces. A higher relative frequency of small trades may reflect broader participation, but it may also make an execution sequence more difficult for liquidity suppliers to interpret. Relative trade size changes the value transferred by a typical small execution relative to a non-small execution and, together with available depth, can affect the price consequences of trading (Pham et al., 2020). Total transaction count captures the overall intensity of trading and information arrival (Jones et al., 1994; Dufour and Engle, 2000), whereas average trade value changes the amount of value transferred per execution. Processing, inventory, immediacy, and adverse-selection considerations therefore provide no general reason for the coefficients within either pair to be equal (Stoll, 1978; Ho and Stoll, 1981; Glosten and Milgrom, 1985; Grossman and Miller, 1988; Huang and Stoll, 1997).

The same literature also motivates examining the coefficient path rather than the contemporaneous association alone. Trades reveal information sequentially, order flow is persistent, inventories need not be redistributed immediately, and liquidity provision itself can have a pronounced term structure (Hasbrouck, 1991; Chordia et al., 2002; Hendershott and Menkveld, 2014; Conrad and Wahal, 2020). Liquidity also has a resiliency dimension: displayed supply and demand can replenish after trading, so the consequences of an execution need not be confined to the instant at which it occurs (Large, 2007; Obizhaeva and Wang, 2013). These mechanisms can generate

persistence in the relation between execution conditions and quoted liquidity. Importantly, they motivate a dynamic empirical specification but do not give the residualized execution states a structural-shock interpretation. Our horizon-specific estimates therefore trace conditional spread associations rather than causal impulse responses.

The paper’s contribution is consequently a measurement result rather than a new theory of trade size. Existing research establishes that transaction frequency, trade size, trader identity, and liquidity dynamics are distinct considerations. We show that using value composition together with total trading value imposes exact pairwise restrictions on the coefficients of four underlying execution margins, test those restrictions under a common projection and common sample, and show that imposing them can reverse liquidity inference. The Chinese A-share market provides a useful application because a stable nominal trade-size classification is observed over a long period in which household and institutional trading coexist. Section 3 describes the setting and the associated measurement issues.

3 Institutional setting, data, and measurement

3.1 China’s A-share market and the small-trade threshold

China’s A-share market provides a useful setting because substantial individual participation coexists with institutional trading, and the two investor groups exhibit distinct trading behavior (Ng and Wu, 2007). A small observed trade may nevertheless originate from a household order or from an institutional child order. We consequently treat trade size as an observable execution characteristic rather than as an identifier of investor type. CSMAR’s long and consistently defined trade-size classification allows us to apply this interpretation over a period spanning substantial changes in participation, trading technology, and market oversight.

The small-trade category consists of buyer- and seller-initiated trades with transaction value below RMB 50,000.¹ Because the cutoff is nominal, stock price mechanically affects classification: holding the number of shares fixed, an otherwise identical execution is more likely to fall below the threshold when the stock price is low. Nominal price is also mechanically related to proportional quoted spreads because a fixed minimum price variation represents a larger fraction of price for lower-priced stocks (Harris, 1994). During the sample period, the trading rules of both the Shanghai and Shenzhen exchanges specified a minimum price increment of RMB 0.01 for A-share orders (Shanghai Stock Exchange, 2023; Shenzhen Stock Exchange, 2023). Price can therefore generate common variation in measured trade-size composition and quoted liquidity.

¹ CSMAR, Factor Research Series, *Individual-Stock Buy–Sell Imbalance Indicator Table (Daily)*, field documentation for B_Num_S. The table documentation classifies an A-share execution below RMB 50,000 as a small trade.

We address this specific measurement concern using predetermined price. Log price measured before the innovation week enters both the common first-stage information set and every spread regression. In Section 5, we additionally allow the count-composition coefficient to vary across groups formed from the predetermined prior-month closing price. These choices address price-induced classification and tick-size confounding; they do not use price as an instrument for trading composition or eliminate other sources of endogeneity.

Recent evidence from China further illustrates why observed trade size should not be equated with trader identity. Zhu and Fang (2023) document distinct persistence and complexity patterns across small and large orders. Lu et al. (2025) construct measures of quantitative-trading activity partly from small-trade execution patterns, motivated by the splitting of parent orders, while Lei et al. (2026) find that the return predictability of small trades in Chinese A-shares is driven primarily by institutional order splitting rather than retail trading. We therefore remain agnostic about the source of an individual small trade and interpret the CSMAR categories as observable execution states.

3.2 Data sources and sample construction

The data come from the China Stock Market and Accounting Research (CSMAR) database. Daily buy–sell imbalance files provide active trading value, transaction counts, trade direction, and order-size categories. Daily spread files provide equal-weighted, time-weighted, and trading-value-weighted relative quoted spreads, together with effective spreads. Daily return files provide stock prices, including the exchange previous close adjusted for ex-right events. Monthly trading and accounting files provide market capitalization, valuation, past returns, turnover, profitability, and accruals.

We combine the historical and recent source files before aggregation, remove duplicate stock-day observations within each source, and require at least three usable trading days in a stock-week. The sample contains nonfinancial Shanghai and Shenzhen A-share stocks that are not designated ST or PT. Continuous variables are winsorized at the pooled 1st and 99th percentiles. We exclude observations with stock prices above RMB 500 so that a small number of extreme nominal-price observations do not dominate the price control or the price-group comparisons.

Panel A of Table 1 reports the sample construction. Matching weekly order-flow and spread data yields 3,129,032 stock-weeks. Requiring positive small- and non-small-trade values and counts together with predetermined price leaves 2,638,021 observations, and requiring the predetermined firm controls leaves 2,605,732. The common first-stage design, which requires 52 weeks of history for all four execution states, uses 1,787,131 stock-weeks for 5,247 stocks over 1,039 estimation weeks. The central nested-model comparison further requires all seven reported future spread outcomes and therefore uses a strict common sample of 1,437,390 stock-weeks for 5,128 stocks.

3.3 Construction of trading and liquidity variables

Our baseline liquidity outcome is the weekly equal-weighted relative quoted spread. For each valid intraday quote record, the relative quoted spread is the ask minus the bid divided by the quote midpoint. We average valid intraday observations within a stock-day and then average the resulting daily spreads within a stock-week:

$$\text{Spread}_{i,d} = \frac{100}{N_{i,d}} \sum_{\ell \in d} \frac{\text{Ask}_{i,\ell} - \text{Bid}_{i,\ell}}{(\text{Ask}_{i,\ell} + \text{Bid}_{i,\ell})/2}, \quad \text{Spread}_{i,w} = \frac{1}{D_{i,w}} \sum_{d \in w} \text{Spread}_{i,d} \quad \#(10)$$

The factor of 100 expresses the spread in percentage points; for example, a value of 0.158 corresponds to 15.8 basis points. The robustness analysis also considers effective, time-weighted quoted, and trading-value-weighted quoted spreads.

Weekly small- and non-small-trade values and transaction counts are obtained by summing the corresponding daily observations before constructing the shares and log-ratio coordinates defined in Section 2.1. Aggregating the underlying values and counts first ensures that each weekly coordinate describes the composition of trading over the week rather than an average of daily ratios.

Predetermined controls include log market value, market-to-book, momentum, one-month reversal, turnover, return on assets, accruals, and log price. The controls are measured before the innovation week. Appendix Table A.2 provides their definitions, timing, units, and data sources.

Table 1: Sample construction and key descriptive statistics

Panel A: Sample construction					
Stage	Stock-weeks		Stocks	Retained (%)	
Matched weekly panel	3,129,032		5,486	100.0	
Positive decomposition states and predetermined price	2,638,021		5,423	84.3	
Predetermined firm controls available	2,605,732		5,306	83.3	
Common first-stage sample	1,787,131		5,247	57.1	
Strict common sample	1,437,390		5,128	45.9	
Panel B: Key variables in the common first-stage sample					
Variable	Mean	SD	P25	Median	P75
Quoted spread	0.1578	0.0908	0.0957	0.1348	0.1933
Small-trade value share	0.2697	0.1520	0.1576	0.2554	0.3638
Small-trade count share	0.7603	0.1669	0.6947	0.8066	0.8768
Count composition	0.9426	0.6925	0.5814	1.0098	1.3876
Relative trade size	-1.7931	0.2102	-1.9075	-1.7623	-1.6458
Log total transaction count	8.9963	0.6782	8.6194	9.0949	9.4969
Log average trade value	10.7080	0.7605	10.1737	10.6169	11.1457

Notes: Panel A reports the construction of the estimation samples. Retention is measured relative to the matched weekly order-flow and spread panel. The common first-stage sample requires positive values and counts for both trade-size categories, predetermined controls, and a common 52-week history for all four execution states. The strict common sample additionally requires nonmissing quoted spreads at all seven reported horizons. Panel B reports selected descriptive statistics for the common first-stage sample. The quoted spread is measured in percentage points. Appendix Tables A.1–A.3 provide sample-selection comparisons, variable definitions, and fuller descriptive statistics.

Panel B of Table 1 illustrates the distinction motivating the decomposition. In the common first-stage sample, small trades account for 27.0% of active trading value but 76.0% of active transactions. A value-based measure therefore represents a substantially different dimension of trading activity from a frequency-based measure. The mean quoted spread is 0.1578 percentage points, or 15.78 basis

points. Appendix Table A.3 reports the full distribution of the execution states, predetermined price, and firm controls.

4 Empirical design

The empirical design has three steps. We first remove predictable variation from each of the four execution states using one common information set. We then compare nested spread specifications that differ only in whether the equal-loading restrictions derived in Section 2.3 are imposed. Finally, we estimate the unrestricted horizon-specific coefficient path and use a split-week design to clarify its temporal interpretation.

4.1 Constructing four-state innovations

The four execution states are persistent and jointly evolve with trading conditions. Our empirical object is therefore not the raw level of each state, but the component that is not linearly predictable from its own history, the histories of the other states, and predetermined firm characteristics. For each $k \in \{NC, RS, TC, AV\}$, we estimate

$$X_{i,w}^k = \alpha_i^k + \lambda_w^k + \sum_{j \in \{NC, RS, TC, AV\}} \sum_{p=1}^{52} \rho_{j,p}^k X_{i,w-p}^j + \Gamma_k' Z_{i,w-1} + u_{i,w}^k \quad \#(11)$$

where $Z_{i,w-1}$ contains the predetermined firm controls described in Section 3.3. The first-stage design is deliberately symmetric. Every state is projected on the same 52 weekly lags of all four states, the same predetermined controls, the same stock and week fixed effects, and the same estimation observations. Thus, for example, the count-composition residual cannot retain variation that is linearly predictable from lagged relative trade size, total transaction count, or average trade value merely because those variables were omitted from its information set. More importantly for the measurement test, applying the same linear projection to every coordinate preserves the accounting identities (6).

We refer to $u_{i,w}^k$ as the innovation in state k . The term is used in a forecasting sense: it is the residual from the common linear projection in equation (11). It is not assumed to be an exogenous structural shock. Contemporaneous news, attention, sentiment, portfolio rebalancing, or other omitted forces may affect both execution composition and quoted liquidity within the same week. The subsequent coefficients are therefore interpreted as conditional associations with residualized changes, not as causal responses to externally generated trading shocks.

Table 2 summarizes the resulting innovations. The common projections explain between 52.8% and 75.4% of within-stock variation across the four states. Residual autocorrelations are economically small, and joint tests provide little evidence of remaining linear dependence on the 52 residual lags. Appendix Table B.1 reports the full cross-state first-stage coefficients and additional diagnostics.

Residualizing predictable histories does not eliminate contemporaneous dependence across the four states. Most notably, the innovations in count composition and average trade value have a

correlation of -0.920. This dependence does not invalidate the four-state regression, but it affects the amount of independent variation available for interpreting any one coefficient. Table 2 therefore reports both marginal and conditional standard deviations, which we use below to distinguish the statistical restriction tests from the economic scaling of the coefficients.

Table 2: First-stage and innovation diagnostics

State	N	Within R^2	Marginal SD	Conditional SD	Ratio	VIF
Count composition	1,787,131	0.7432	0.2362	0.0878	0.3715	7.24
Relative trade size	1,787,131	0.5281	0.0967	0.0855	0.8839	1.28
Total transaction count	1,787,131	0.7541	0.1972	0.1744	0.8845	1.28
Average value per trade	1,787,131	0.7059	0.2759	0.0978	0.3546	7.95
Innovation correlation	Count composition	Relative size	Total count	Average trade value		
Count composition	1.000	0.199	-0.442	-0.920		
Relative size	0.199	1.000	0.006	-0.340		
Total count	-0.442	0.006	1.000	0.432		
Average trade value	-0.920	-0.340	0.432	1.000		

Notes: The table summarizes the four common first-stage projections in equation (11). Each projection uses the same 52-week histories of all four execution states, predetermined controls, stock and week fixed effects, and estimation observations. Marginal SD is the standard deviation of the resulting innovation. Conditional SD is the residual standard deviation from projecting that innovation on the other three contemporaneous innovations; Ratio is the conditional SD divided by the marginal SD, and VIF is the corresponding variance-inflation factor. The lower panel reports contemporaneous innovation correlations. Appendix Table B.1 reports the underlying cross-state first-stage coefficients and joint lag tests.

4.2 Nested measurement specifications

The primary empirical test compares three nested specifications while holding the estimation sample, outcome, predetermined controls, spread history, fixed effects, and clustering scheme fixed. The models differ only in which of the equal-loading restrictions in equation (9) are imposed:

$$\begin{aligned}
M0: \text{Spread}_{i,w+h} &= \tilde{\beta}_h^{VC} u_{i,w}^{VC} + \tilde{\beta}_h^{TV} u_{i,w}^{TV} + \dots, \\
M1: \text{Spread}_{i,w+h} &= \beta_h^{NC} u_{i,w}^{NC} + \beta_h^{RS} u_{i,w}^{RS} + \tilde{\beta}_h^{TV} u_{i,w}^{TV} + \dots, \\
M2: \text{Spread}_{i,w+h} &= \beta_h^{NC} u_{i,w}^{NC} + \beta_h^{RS} u_{i,w}^{RS} + \beta_h^{TC} u_{i,w}^{TC} + \beta_h^{AV} u_{i,w}^{AV} + \dots.
\end{aligned} \tag{12}$$

The omitted terms are identical across the three models and are written explicitly below.

M0 is the fully aggregated specification: value composition combines relative transaction frequency with relative trade size, and total trading value combines total transaction count with average trade value. It therefore imposes both equal-loading restrictions. M1 relaxes the composition restriction by allowing count composition and relative trade size to enter separately but retains total trading value as the aggregated scale regressor. M2 relaxes both restrictions and allows all four underlying margins to enter separately. The M0–M1–M2 sequence therefore identifies whether any change in liquidity inference comes from separating composition alone or requires separating trading scale as well.

We test the restrictions in the original coordinate units. At each horizon, the composition test evaluates

$$H_0: \beta_h^{NC} = \beta_h^{RS},$$

the scale test evaluates

$$H_0^S: \beta_h^{TC} = \beta_h^{AV},$$

and a joint Wald test imposes both equalities. These tests must be conducted before standard-deviation scaling because coefficient equality is defined by the accounting identities in the original coordinate units. We report Holm-adjusted p -values across the seven horizons within each restriction family (Holm, 1979).

For $h \in \{0, 1, 2, 4, 13, 26, 52\}$, the unrestricted M2 specification is

$$\text{Spread}_{i,w+h} = \alpha_i^h + \lambda_w^h + \sum_{k=1}^4 \beta_h^k u_{i,w}^k + \sum_{r=1}^{52} \psi_{h,r} \text{Spread}_{i,w-r} + \Theta_h' Z_{i,w-1} + \varepsilon_{i,w+h} \quad \#(13)$$

Here, $h = 0$ denotes the innovation week and $h > 0$ denotes the quoted spread in a subsequent week. The terms α_i^h and λ_w^h are horizon-specific stock and week fixed effects, $Z_{i,w-1}$ contains the predetermined firm controls, and the 52 lagged spreads capture the stock's prior liquidity history.

We estimate equation (13) separately at each horizon rather than imposing a complete dynamic system (Jordà, 2005; Plagborg-Møller and Wolf, 2021; Montiel Olea and Plagborg-Møller, 2021; Jordà and Taylor, 2025). Each horizon re-estimates the stock and week fixed effects, predetermined controls, and spread lags. Standard errors are clustered by stock and week (Cameron et al., 2011). The sequence $\{\beta_h^k\}$ therefore describes how the conditional association between the innovation in state k and the level of the quoted spread varies with the horizon.

Because the dependent variable is the spread level rather than the change in the spread, β_h^k should not be interpreted as the incremental effect occurring between weeks $h - 1$ and h . To compare adjacent horizons, we estimate the corresponding regression using the change in the spread outcome, which accounts for covariance between the two horizon-specific coefficients.

The restriction tests use raw innovation units, but the four coordinates have different scales. For economic interpretation, we multiply each estimated coefficient by the marginal standard deviation of its innovation and convert percentage-point spreads to basis points. A reported marginal-SD coefficient therefore answers: how much wider or narrower is the quoted spread associated with a one-standard-deviation innovation in that state, holding the other three innovations fixed in the regression?

Because the four innovations remain contemporaneously correlated, a marginal standard deviation can substantially exceed the variation in one innovation that is linearly distinct from the other three. We therefore also define

$$\hat{\sigma}_{k|-k} = \hat{\sigma}_k \sqrt{1 - R_{k|-k}^2} = \frac{\hat{\sigma}_k}{\sqrt{\text{VIF}_k}} \quad \#(14)$$

where $R_{k|-k}^2$ is obtained by projecting innovation k on the other three contemporaneous innovations. We refer to $\hat{\sigma}_{k|-k}$ as the conditional standard deviation.

This scaling is particularly informative for count composition. Its marginal standard deviation is 0.236, but its conditional standard deviation is only 0.088 because count composition is highly

correlated with average trade value. We therefore report the focal count-composition coefficient in both marginal- and conditional-SD units. The latter is a scaling device for economic magnitude; it does not alter the estimated coefficient or the Wald tests.

Neither the first-stage residualization nor the horizon-by-horizon regression supplies structural identification. The first-stage innovations remove linear predictability from the specified information set, but they may still be correlated with contemporaneous omitted determinants of liquidity. We therefore use “innovation” as shorthand for a residualized change and interpret β_h^k as a horizon-specific conditional association, not as a causal impulse response.

4.3 Split-week temporal-ordering diagnostic

The weekly specification establishes the horizon at which the count-composition coefficient is observed, but it cannot determine the ordering of trading composition and quote formation within the innovation week. A weekly average may combine an early association, subsequent propagation, and partial reversal in the same observation. We therefore divide eligible stock-weeks into an early window (Monday–Tuesday) and a late window (Wednesday–Friday).

We require valid state and spread observations on both early trading days and on at least two trading days in the late window. The four execution states are reconstructed separately within each window, but their innovations are formed using the same preceding 52 full-week histories. This choice preserves a common predetermined information set and avoids conditioning the first stage on the number or location of trading days within shortened holiday weeks. Predetermined controls, stock and week fixed effects, spread histories, and two-way clustering otherwise follow the weekly specification.

The split-week design addresses three questions. First, we re-estimate M0–M2 using the early-window spread to determine whether the sign reversal is already present during early-week quote formation. Second, within M2, we relate the early-window count-composition innovation to the late-window spread, both with and without conditioning on the early spread, and to the late-minus-early change in the spread. These specifications ask whether the early association appears to propagate through the remainder of the week. Third, we reverse the timing by relating the early spread to late-window innovations. A material reverse-timing coefficient would caution against interpreting the forward association as directional transmission. All split-week comparisons use the same 1,636,160 stock-weeks.

5 Main Results

This section establishes the paper’s two main empirical results. First, the equal-loading restrictions implied by the aggregated value measures are strongly rejected, and relaxing both restrictions reverses the sign assigned to small-trade frequency. Second, the unrestricted four-margin model reveals distinct signs and dynamic patterns that the aggregated measures conceal. All comparisons in this

section use the same 1,437,390 stock-weeks and otherwise identical controls, fixed effects, spread lags, and inference.

5.1 Aggregation restrictions and the sign reversal

Table 3 provides the central test. The three specifications differ only in the restrictions imposed on the four underlying execution margins. M0 leaves both value composition and trading scale aggregated. M1 separates value composition into count composition and relative trade size but continues to combine total transaction count with average trade value. M2 allows all four margins to enter separately.

The sequence produces a sharp change in inference. In M0, a one-marginal-standard-deviation innovation in value composition is associated with a contemporaneous quoted spread that is 0.612 basis points narrower. Decomposing value composition alone does not overturn this result: in M1, the count-composition coefficient remains negative at -0.343 basis points. Only when the activity-scale restriction is also relaxed in M2 does the count-composition coefficient turn positive, to 0.278 basis points. Thus, the reversal does not arise simply from replacing a value-based measure with a count-based measure. It requires separating both relative execution composition and the scale at which trading occurs.

The restriction tests show that the change in sign reflects economically different component loadings rather than a change in sample or specification. At the impact horizon, equality between the two composition coefficients is rejected with $F = 1348.8$, equality between the two scale coefficients with $F = 1020.0$, and the two restrictions jointly with $F = 1157.3$. After Holm adjustment across the seven reported horizons, the composition restriction is rejected at every horizon. The scale restriction is rejected through week 26, and the joint restriction remains rejected at week 52. The improvement in within- R^2 is comparatively small. The importance of the decomposition is therefore not primarily predictive fit; it is that aggregation imposes coefficient restrictions that materially change the economic interpretation.

Table 3: Nested measurement models on the strict common sample

	$h = 0$	$h = 1$	$h = 2$	$h = 4$	$h = 13$	$h = 26$	$h = 52$
M0: unseparated value composition	-0.6120*** (0.0234)	-0.2696*** (0.0175)	-0.1801*** (0.0164)	-0.1169*** (0.0186)	-0.0135 (0.0162)	-0.0016 (0.0162)	0.0038 (0.0195)
M1: count composition, scale pooled	-0.3428*** (0.0245)	-0.1238*** (0.0187)	-0.0794*** (0.0171)	-0.0428** (0.0177)	0.0293 (0.0181)	0.0211 (0.0186)	0.0276 (0.0187)
M2: count composition, marginal SD	0.2782*** (0.0179)	0.1423*** (0.0221)	0.0937*** (0.0212)	0.0655*** (0.0240)	0.0719*** (0.0231)	0.0781*** (0.0229)	0.0180 (0.0250)
M2: count composition, conditional SD	0.1034*** (0.0067)	0.0529*** (0.0082)	0.0348*** (0.0079)	0.0243*** (0.0089)	0.0267*** (0.0086)	0.0290*** (0.0085)	0.0067 (0.0093)

	$h = 0$	$h = 1$	$h = 2$	$h = 4$	$h = 13$	$h = 26$	$h = 52$
Composition: $\beta^{NC} = \beta^{RS}$	< 0.001	< 0.001	< 0.001	< 0.001	< 0.001	0.0018	0.0151
Scale: $\beta^{TC} =$ β^{AV}	< 0.001	< 0.001	< 0.001	< 0.001	0.0204	0.0039	0.5733
Both restrictions jointly	< 0.001	< 0.001	< 0.001	< 0.001	< 0.001	< 0.001	0.0444
M0	0.8945	0.8561	0.8270	0.7798	0.6335	0.4973	0.3122
M1	0.8955	0.8565	0.8271	0.7799	0.6336	0.4973	0.3122
M2	0.8986	0.8570	0.8274	0.7800	0.6336	0.4973	0.3122

Notes: All specifications use the same 1,437,390 stock-weeks and identical outcomes, predetermined controls, 52 spread lags, stock and week fixed effects, and two-way clustered standard errors. M0 leaves both value composition and trading scale aggregated. M1 decomposes value composition but retains total trading value as the aggregated scale regressor. M2 estimates all four underlying margins jointly. Panel A reports basis-point associations for one marginal-standard-deviation innovation, except for the explicitly labeled conditional-SD row. Panel B reports Holm-adjusted p-values for the raw-unit equal-loading restrictions derived in Section 2.3. Panel C reports within- R^2 . *** and ** denote significance at 1% and 5%.

Figure 1 makes the economic contrast visible. The coarser M0 and M1 paths begin below zero, whereas the unrestricted M2 path begins above zero. The figure also shows that all three coefficients converge toward zero at long horizons. The measurement result is therefore a reversal in the sign and interpretation of the front-end association rather than a claim of permanently wider spreads.

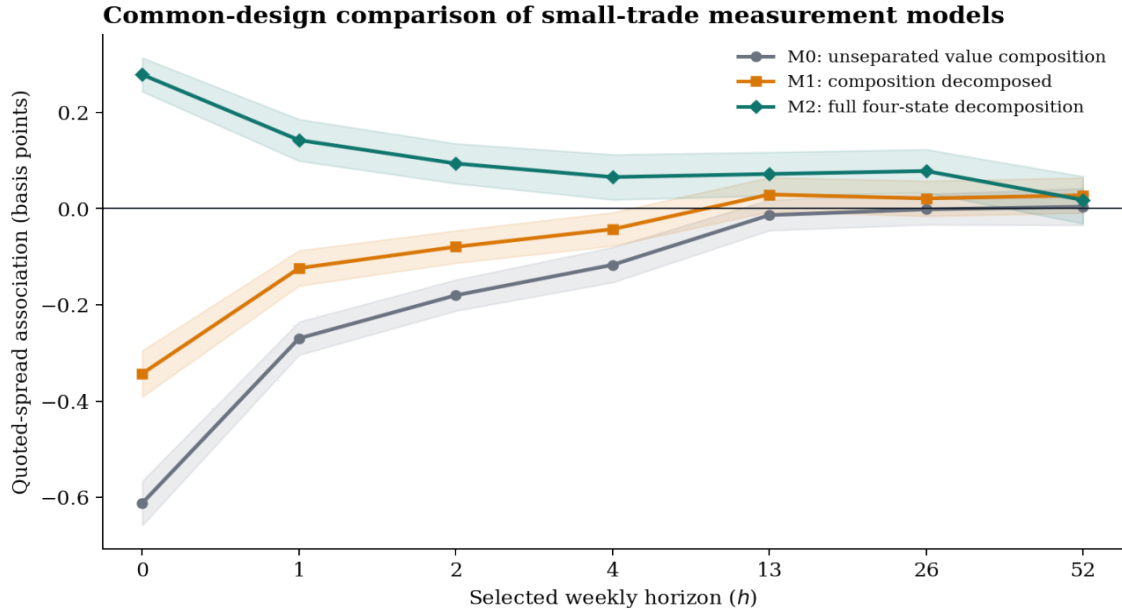


Figure 1: Aggregation and the sign of the small-trade frequency association

The figure plots the focal coefficients from M0, M1, and M2 on the strict common sample. M0 leaves value composition and trading scale aggregated; M1 decomposes value composition only; M2 decomposes both composition and scale. Coefficients are expressed in basis points per marginal standard deviation, and shaded regions are pointwise 95% confidence intervals.

The magnitude of the unrestricted count-composition coefficient should be interpreted in light of contemporaneous dependence among the four innovations. Count composition has a marginal standard deviation of 0.236 but a conditional standard deviation of 0.088, reflecting its strong correlation with average trade value. The M2 impact coefficient therefore corresponds to 0.278 basis points per marginal standard deviation and 0.103 basis points per conditional standard deviation. The latter is about 0.66% of the sample mean quoted spread and provides a more conservative scale for variation in count composition that is not linearly shared with the other execution margins.

The standalone magnitude is modest. The economically consequential finding is instead the change in sign: the aggregated specification associates greater small-trade value composition with narrower spreads, whereas the unrestricted specification associates a higher relative frequency of small trades with wider spreads. Aggregation therefore changes which liquidity inference is assigned to the frequency margin.

5.2 The four margins behind the reversal

The unrestricted model shows why the aggregated coefficients are difficult to interpret. Table 4 reports the four coefficient paths jointly, and Figure 2 displays them. At the impact horizon, the two components of value composition have opposite signs. Count composition is associated with a 0.278-basis-point wider spread, whereas relative trade size is associated with a 0.207-basis-point narrower spread. The two components of trading scale also have opposite signs: total transaction count is associated with a 0.499-basis-point narrower spread, while average trade value is associated with a 0.321-basis-point wider spread.

These differences give empirical content to the restrictions derived in Section 2.3. Value composition forces relative transaction frequency and relative trade size to share a coefficient even though their unrestricted impact coefficients have opposite signs. Total trading value similarly forces total transaction count and average trade value to share a coefficient despite sharply different impact associations. The aggregated regressors therefore do more than summarize highly correlated variables: they suppress economically distinct margins whose conditional associations with quoted spreads differ in sign as well as magnitude.

Table 4: Four execution margins and quoted-spread coefficient paths

	$h = 0$	$h = 1$	$h = 2$	$h = 4$	$h = 13$	$h = 26$	$h = 52$
Count composition	0.2782*** (0.0179)	0.1423*** (0.0221)	0.0937*** (0.0212)	0.0655*** (0.0240)	0.0719*** (0.0231)	0.0781*** (0.0229)	0.0180 (0.0250)
Relative trade size	-0.2065*** (0.0081)	-0.1117*** (0.0077)	-0.0780*** (0.0073)	-0.0577*** (0.0101)	-0.0237** (0.0097)	-0.0033 (0.0099)	-0.0178 (0.0119)
Total transaction count	-0.4988*** (0.0137)	-0.3734*** (0.0113)	-0.3235*** (0.0098)	-0.2705*** (0.0093)	-0.1762*** (0.0107)	-0.1512*** (0.0109)	-0.0977*** (0.0108)
Average trade value	0.3209*** (0.0195)	-0.0860*** (0.0235)	-0.1687*** (0.0213)	-0.2008*** (0.0229)	-0.1766*** (0.0234)	-0.1182*** (0.0240)	-0.1525*** (0.0257)
Observations	1,437,390	1,437,390	1,437,390	1,437,390	1,437,390	1,437,390	1,437,390
Within R^2	0.8986	0.8570	0.8274	0.7800	0.6336	0.4973	0.3122

Notes: Entries are basis-point coefficients for one marginal-standard-deviation innovation. Count composition, relative trade size, total transaction count, and average trade value enter jointly in every regression. All horizons use the strict common sample of 1,437,390 stock-weeks and include predetermined controls, 52 lags of the quoted spread, stock and week fixed effects, and two-way clustered standard errors. Horizon $h = 0$ denotes the innovation week; positive horizons denote subsequent weekly quoted spreads. *** and ** denote significance at 1% and 5%.

Figure 2 also shows that the four margins differ over time. The positive count-composition association is largest in the innovation week and declines sharply thereafter. The negative relative-size coefficient also attenuates and is close to zero by the medium horizons. Total transaction count

remains negatively associated with spreads throughout the reported horizon. Average trade value is different again: its coefficient is positive contemporaneously but turns negative from week one onward. Aggregation can therefore obscure not only the sign of a component association but also its dynamic profile.

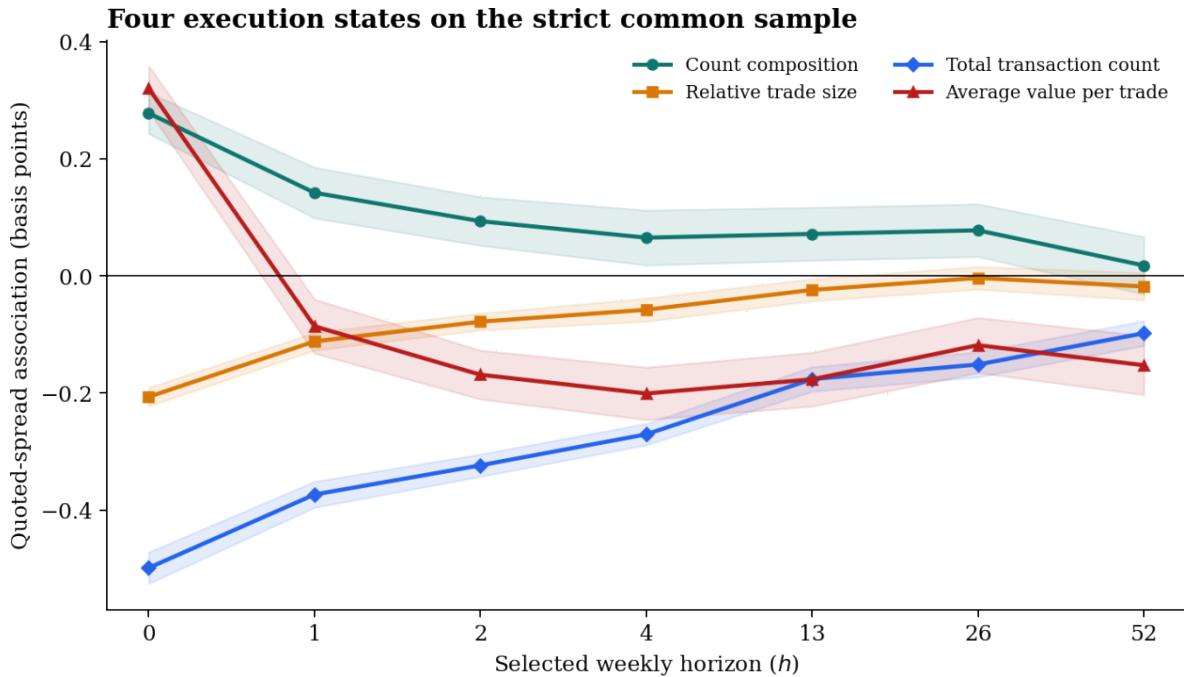


Figure 2: Four execution margins and quoted-spread coefficient paths

The figure plots the horizon-specific coefficients from the unrestricted four-margin specification. All four innovations enter each regression jointly on the strict common sample. Coefficients are expressed in basis points per marginal standard deviation, and shaded regions are pointwise 95% confidence intervals.

The signs are consistent with distinct trading margins, but they should not be read as separately identified mechanisms. Holding relative trade size and aggregate activity fixed, a rise in count composition means that small trades occur more frequently relative to non-small trades; its positive coefficient is consistent with greater processing or continuation concerns. The negative total-count coefficient is instead consistent with greater overall trading activity accompanying a more liquid market. Relative trade size and average trade value capture different dimensions of value transferred per execution. These interpretations explain why equal loadings are economically restrictive, but the regressions do not identify the underlying trading motive.

5.3 Dynamic shape of the count-composition association

The focal count-composition coefficient is strongly front-loaded. It falls from 0.278 basis points in the innovation week to 0.142 after one week and 0.094 after two weeks. The impact-to-week-1 decline is -0.136 basis points ($p < 0.001$), and the week-1-to-week-2 decline is -0.049 basis points ($p < 0.001$). The subsequent week-2-to-week-4 change is smaller and statistically insignificant ($p = 0.116$), and the coefficients are statistically similar from weeks 4 through 26. The coefficient then

falls from 0.078 basis points at week 26 to 0.018 at week 52, a difference of -0.060 basis points ($p = 0.014$). By week 52, the coefficient itself is statistically indistinguishable from zero.

The pooled path is therefore characterized by a contemporaneous maximum, rapid attenuation over the first two weeks, and a modest medium-horizon tail that disappears by the one-year horizon. These estimates are horizon-specific coefficients on the level of the quoted spread. A positive coefficient at a later horizon does not, by itself, imply continued or delayed spread pressure: it may instead reflect persistence in the spread state established during the innovation week. The next subsection uses within-week and post-impact diagnostics to distinguish these interpretations.

5.4 Locating the association in time

The weekly coefficient path shows that the count-composition association is front-loaded, but weekly horizons alone do not reveal where the association is formed. In particular, positive coefficients at later horizons may represent additional spread adjustment or simply persistence of the spread state established during the innovation week. We investigate this distinction in two steps.

We first condition each positive-horizon projection on the quoted spread observed during the innovation week. Because that spread is jointly determined with the innovation, the exercise is diagnostic rather than a causal mediation test. Table 5 shows that, once the impact-week spread is included, the count-composition coefficient is no longer positive at any subsequent horizon. It is statistically indistinguishable from zero at weeks 1, 13, 26, and 52 and modestly negative at weeks 2 and 4. The positive medium-horizon coefficients in the baseline specification therefore appear to be largely inherited from the spread state established during the innovation week rather than generated by a distinct positive association that emerges later.

Table 5: Conditioning subsequent-horizon coefficients on the innovation-week spread

Specification	(h=1)	(h=2)	(h=4)	(h=13)	(h=26)	(h=52)
Baseline coefficient	0.1423***	0.0937***	0.0655***	0.0719***	0.0781***	0.0180
	(0.0221)	(0.0212)	(0.0240)	(0.0231)	(0.0229)	(0.0250)
Within R^2 : baseline	0.8570	0.8274	0.7800	0.6336	0.4973	0.3122
Conditioning on impact-week spread	-0.0166	-0.0404**	-0.0462**	-0.0131	0.0094	-0.0316
	(0.0180)	(0.0173)	(0.0220)	(0.0219)	(0.0214)	(0.0249)
Within R^2 : conditioned	0.8901	0.8510	0.7964	0.6430	0.5035	0.3155

Notes: Entries are basis-point coefficients on the count-composition innovation estimated on the strict common sample. The baseline specification is the unrestricted four-margin model. The conditioned specification additionally includes the quoted spread observed in the innovation week. Because that spread is jointly determined with the innovation, the conditioned specification is used only as a propagation diagnostic and is not interpreted as a causal mediation design. Within- R^2 is reported for each horizon-specific regression. *** and ** denote significance at 1% and 5%.

This finding shifts attention to the innovation week itself. Weekly averaging may still combine early quote formation with subsequent reversal, so we divide each eligible week into Monday–Tuesday and Wednesday–Friday windows. Panel A of Table 6 shows that the measurement reversal is already present during the first two trading days. On the same 1,636,160 stock-weeks, M0 and M1 associate the early-week spread with coefficients of -0.720 and -0.499 basis points, respectively,

whereas the unrestricted M2 count-composition coefficient is positive at 0.129 basis points. The composition, scale, and joint equal-loading restrictions are all strongly rejected. The sign reversal therefore does not arise because weekly averaging combines an initially negative association with a later positive one; it is already present in early-week quote formation.

Panel B provides little evidence that the early-week association propagates into the remainder of the week. The early count-composition innovation is associated with only 0.015 basis points of the Wednesday–Friday spread, and the coefficient falls to essentially zero after conditioning on the early-week spread. The late-minus-early coefficient is negative, indicating that the early association recedes rather than builds over the remainder of the week. Moreover, the reverse-timing coefficient is larger than the corresponding forward coefficient. These results locate the unrestricted positive association near early quote formation but do not establish directional transmission from early trading composition to later liquidity.

Table 6: Within-week location of the measurement reversal

Specification	Coefficient	Standard error	p-value	Within R^2
<i>Panel A: Early-week spread</i>				
M0: unseparated value composition	-0.7200***	0.0362	< 0.001	0.5457
M1: count composition, scale pooled	-0.4989***	0.0287	< 0.001	0.5460
M2: unrestricted count composition	0.1286***	0.0261	< 0.001	0.5475
Early innovation → late spread	0.0152	0.0377	0.688	0.6788
Same, conditioning on early spread	0.0008	0.0299	0.979	0.6862
Early innovation → late-minus-early spread	-0.1135***	0.0343	0.001	0.0058
Late innovation → early spread	0.0710*	0.0395	0.073	0.5421

Notes: Coefficients and standard errors are in basis points per marginal standard deviation. Early denotes Monday–Tuesday and late denotes Wednesday–Friday. Panel A re-estimates M0–M2 using the early-window quoted spread. Panel B reports temporal-ordering diagnostics from the unrestricted four-margin specification. All rows use the same 1,636,160 stock-weeks, common predetermined information set, 52 full-week spread lags, stock and week fixed effects, and two-way clustering by stock and week. The late-minus-early specification uses the within-week change in the quoted spread as the dependent variable. *** and * denote significance at 1% and 10%.

Taken together, the weekly and split-week evidence points to a front-loaded association. The positive coefficients observed at later weekly horizons largely inherit the spread state formed near the innovation week, while the within-week evidence does not show clean subsequent propagation. We therefore interpret the estimated path as a conditional term structure of spread associations rather than as a structurally identified liquidity response. Additional filtering for short-run dependence in the split-window residuals leaves this temporal-ordering conclusion unchanged: Appendix C.2 reports the results.

5.5 Predetermined price and the nominal classification problem

The fixed RMB 50,000 cutoff creates a specific measurement concern. Because classification depends on nominal transaction value, holding share quantity fixed, a trade is more likely to be classified as small when the stock price is low. Nominal price is also mechanically related to proportional quoted

spreads because the RMB 0.01 minimum tick is coarser relative to price for lower-priced stocks. Price can therefore generate common variation in measured trade-size composition and quoted liquidity even without a direct relation between the underlying execution margin and liquidity.

The baseline design addresses this source of mechanical confounding in two ways. Predetermined log price enters both the common first-stage information set and every spread regression, so contemporaneous changes in execution composition cannot determine the price control. We then allow the count-composition coefficient itself to vary across predetermined price groups. This second exercise is useful because a linear price control need not absorb heterogeneity associated with the fixed nominal threshold or the proportional tick size.

Table 7 and Figure 3 show that the impact association is not monotonically concentrated among the lowest-priced stocks. The largest impact coefficient occurs in the RMB 5–10 group, at 0.419 basis points, compared with 0.338 basis points below RMB 5 and 0.212 basis points at RMB 10 or above. The middle-price group also has the largest coefficient through week 13. A purely mechanical explanation in which low nominal prices generate the baseline sign reversal through the classification rule therefore does not fit the short-horizon pattern.

Nominal price is more closely related to the persistence of the coefficient. Among stocks below RMB 5, the count-composition coefficient remains 0.193 basis points at week 26 and 0.104 basis points at week 52. For stocks priced at RMB 10 or above, the corresponding coefficients are 0.043 and essentially zero. The low-minus-high difference is 0.150 basis points at week 26 ($p=0.002$) and 0.107 basis points at week 52 ($p=0.024$). Low nominal prices therefore appear more relevant for the persistence of the spread association than for the existence of the impact-week sign reversal.

Table 7: Predetermined price and the count-composition coefficient path

Price group	N	Mean spread	(h=0)	(h=4)	(h=13)	(h=26)	(h=52)
Below RMB 5	300,591	30.51	0.3376*** (0.0382)	0.0800* (0.0480)	0.1347** (0.0551)	0.1927*** (0.0502)	0.1042** (0.0514)
RMB 5 to below 10	577,666	16.56	0.4186*** (0.0233)	0.2017*** (0.0272)	0.1635*** (0.0269)	0.1404*** (0.0293)	0.0322 (0.0285)
RMB 10 or above	908,874	10.42	0.2116*** (0.0154)	0.0877*** (0.0188)	0.0687*** (0.0188)	0.0425** (0.0184)	-0.0029 (0.0254)
Low minus high			0.1260*** (0.0401)	-0.0077 (0.0460)	0.0659 (0.0540)	0.1502*** (0.0482)	0.1071** (0.0473)
Within R^2 , pooled model			0.9049	0.7890	0.6453	0.5060	0.3184

Notes: Price groups are defined using the predetermined prior-month closing price. Coefficients and standard errors are in basis points per marginal standard deviation of count composition. At each horizon, group-specific coefficients and their differences are estimated in a single pooled interaction regression with the baseline four-margin controls. Mean quoted spreads are reported in basis points. The low-minus-high row reports the coefficient difference between stocks priced below RMB 5 and those priced at RMB 10 or above. ***, **, and * denote significance at 1%, 5%, and 10%.

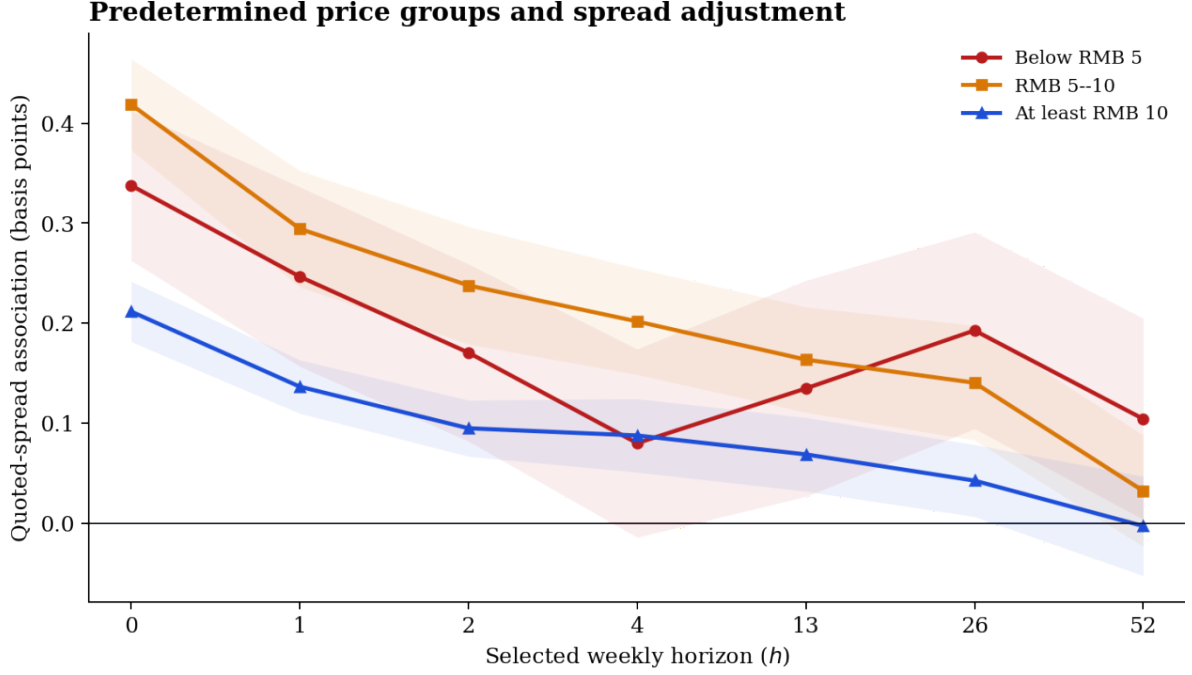


Figure 3: Predetermined price and the count-composition coefficient path

The figure plots group-specific coefficients on the count-composition innovation from pooled interaction regressions. Price groups are formed using the prior-month closing price, measured before the innovation week. Coefficients are expressed in basis points per marginal standard deviation, and shaded regions are pointwise 95% confidence intervals.

These results distinguish two roles of price. Conditioning on predetermined price and observing a positive impact coefficient in every price group make it difficult to attribute the central sign reversal solely to the fixed nominal cutoff. At the same time, the greater long-horizon persistence among low-priced stocks is consistent with the coarser proportional price grid affecting displayed-spread normalization. Because price is not randomly assigned and the price groups differ along other dimensions, the exercise addresses a specific price-induced measurement confound; it does not eliminate all sources of endogeneity or provide structural identification.

6 Robustness and stability

The main results establish the measurement reversal, locate the positive count-composition association near the innovation week, and address the mechanical role of nominal price. We now ask whether the result depends on the common-sample restriction, the measurement of liquidity, the treatment of common shocks, the historical period, or alternative descriptions of small-trade activity.

6.1 Alternative samples, liquidity measures, and common factors

Panel A of Table 8 relaxes the strict common-sample requirement and uses all available observations at each horizon. The count-composition coefficient remains positive on impact at 0.266 basis points, remains positive at weeks 4 and 13, and is statistically indistinguishable from zero at week 52. These

estimates closely track the common-sample results, indicating that horizon-specific sample turnover does not account for the front-loaded coefficient path.

Panel B replaces the equal-weighted quoted spread with the effective spread, time-weighted quoted spread, and trading-value-weighted quoted spread. Each measure yields a positive impact coefficient, smaller coefficients at later horizons, and no statistically significant association at week 52. The sign and attenuation pattern are therefore not specific to one method of measuring or aggregating liquidity.

Panel C addresses the possibility that liquidity and order flow contain common components whose exposures vary across stocks (Chordia et al., 2000; Hasbrouck and Seppi, 2001). We allow such common shocks to enter through interactive fixed effects (Bai, 2009). On identical long-panel samples, the one- and two-factor estimates preserve about 90–92% of the same-sample two-way-fixed-effect impact coefficient and about 87–88% of the corresponding week-4 coefficient. The one-factor estimate remains positive at week 13 and is close to zero at week 52. Allowing for heterogeneous exposure to latent common factors therefore reduces the magnitude modestly but does not remove the short-horizon count-composition association.

Table 8: Sample, liquidity-measure, and fixed-effect checks

Specification	(h=0)	(h=4)	(h=13)	(h=52)
<i>Panel A: Horizon-specific samples</i>				
Quoted spread	0.2661*** (0.0156)	0.0849*** (0.0209)	0.0850*** (0.0213)	0.0211 (0.0245)
Within R^2	0.9041	0.7870	0.6427	0.3165
<i>Panel B: Alternative liquidity outcomes</i>				
Effective spread	0.2439*** (0.0162)	0.0837*** (0.0207)	0.0852*** (0.0214)	0.0211 (0.0240)
Within R^2 : effective spread	0.8957	0.7853	0.6474	0.3260
Time-weighted quoted spread	0.3112*** (0.0171)	0.1029*** (0.0225)	0.0954*** (0.0232)	0.0287 (0.0265)
Within R^2 : time weighted	0.8867	0.7556	0.6114	0.2992
Trading-value-weighted spread	0.5119*** (0.0250)	0.1290*** (0.0236)	0.1136*** (0.0242)	0.0334 (0.0271)
Within R^2 : value weighted	0.8297	0.7013	0.5703	0.2747
<i>Panel C: Interactive fixed effects on identical samples</i>				
TWFE, same sample	0.2715*** (0.0163)	0.0968*** (0.0217)	0.0918*** (0.0218)	0.0234 (0.0248)
Within R^2 : TWFE	0.9149	0.8067	0.6683	0.3303
One-factor IFE	0.2434*** (0.0139)	0.0841*** (0.0145)	0.0992*** (0.0188)	0.0090 (0.0235)
Two-factor IFE	0.2491*** (0.0127)	0.0852*** (0.0127)	— —	— —

Notes: Entries are basis-point coefficients on the count-composition innovation. Panel A uses all available observations separately at each horizon. Panel B replaces the baseline equal-weighted quoted spread with alternative liquidity measures. Panel C compares two-way and interactive fixed-effects estimators on identical long-panel samples. The reported within- R^2 in Panel C corresponds to the same-sample two-way fixed-effects regression; no directly comparable interactive-fixed-effect R^2 is reported. *** denotes significance at 1%.

6.2 Stability across market eras

The pooled sample spans substantial changes in investor participation, execution technology, and market oversight. We therefore re-estimate all four first-stage projections separately for 2005–2011,

2012–2018, and 2019–2025 and construct an era-specific common sample in each period. The measurement conclusion is stable. M0 and M1 produce negative impact coefficients in every era, while the unrestricted M2 count-composition coefficient is positive in the two later eras and statistically indistinguishable from zero in 2005–2011. More importantly, the joint equal-loading restrictions are rejected at the impact horizon in all three eras.

The timing of the unrestricted association is less stable. In 2005–2011, the positive count-composition coefficient appears at week 1 rather than contemporaneously. In 2012–2018, it remains positive through week 13, whereas in 2019–2025 it is concentrated near impact and largely dissipates after one week. Formal tests reject equality of the count-composition coefficient across eras from impact through week 13 but not at weeks 26 or 52. Aggregation therefore changes inference more consistently than the exact timing of the unrestricted coefficient. The pooled estimates should be interpreted as an average conditional term structure rather than as a time-invariant liquidity relation.

6.3 Direction and absolute trading value

Two additional specifications clarify what the positive count-composition coefficient represents. We first ask whether it primarily reflects buy–sell direction. Because buy- and sell-side count shares are highly correlated, estimating two complete directional four-state systems produces unstable comparisons. We instead augment the baseline four-margin model with buy-minus-sell contrast coordinates. The count-composition path is essentially unchanged. The directional count contrast is -0.036 basis points on impact ($p < 0.001$), consistent with a somewhat stronger seller-side association, but it is insignificant at weeks 1, 2, and 4 and only intermittently significant thereafter. Direction therefore refines the contemporaneous association but does not account for the main count-composition path.

We next ask whether the result is simply an association with greater small-trade value. Replacing relative composition with innovations in absolute small-, medium-, and large-trade values produces the opposite impact sign: the small-trade value coefficient is -0.378 basis points on impact, remains negative at week 4, and is statistically indistinguishable from zero by week 13. Greater small-trade value by itself therefore does not reproduce the positive count-composition coefficient. The focal result concerns the relative frequency with which small trades occur after relative trade size and aggregate trading scale are separated.

7 Interpretation and broader implications

The unrestricted count-composition coefficient pertains to a specific execution margin: the frequency of small trades relative to non-small trades, conditional on relative average trade size and the overall scale of trading activity. It should therefore not be interpreted as a coefficient on “small trading” in general. Relative trade size, total transaction count, and average trade value have different signs and dynamic profiles, and recombining these margins into value-based measures changes the resulting

liquidity inference. The economic interpretation therefore depends on which underlying margin moves.

The decomposition identifies observable execution margins, not the structural motives that generate them. A rise in small-trade frequency may reflect household participation, institutional order splitting, attention-driven trading, or another source of concentrated order flow. Likewise, the estimated innovations are residualized changes relative to a predetermined information set rather than externally generated shocks. Contemporaneous news, attention, sentiment, portfolio rebalancing, or other omitted forces may affect both execution composition and liquidity. The estimated coefficients therefore describe conditional relationships among execution states and quoted spreads; they do not identify the causal effect of exogenously changing small-trade frequency.

The measurement lesson extends beyond the Chinese setting and beyond trade-size classifications. Whenever transaction activity is summarized by the value share of an observed category, that share combines the category's relative transaction frequency with its relative average transaction size. An accompanying aggregate-value measure can similarly combine total transaction count with average transaction value. If the underlying margins have unequal associations with the outcome, replacing them with the aggregated measures imposes restrictions that can obscure or even reverse the inference attached to the category. Separating relative composition from aggregate scale is therefore a useful first step before assigning economic meaning to value-based transaction measures.

8 Conclusion

This paper studies how aggregation affects liquidity inference from small-trade measures. An exact value-count identity decomposes small-trade value composition into relative transaction frequency and relative average trade size, while a second identity decomposes total trading value into total transaction count and average trade value. Under a common linear projection, regressions using the two aggregated value measures impose equal-loading restrictions within each pair. The data strongly reject those restrictions.

On the same 1,437,390 stock-weeks, the aggregated value-composition innovation is associated with narrower contemporaneous quoted spreads, whereas the unrestricted count-composition coefficient is positive. The sign reversal appears only after both execution composition and trading scale are decomposed. The positive unrestricted association is front-loaded: later weekly coefficients largely inherit the spread state established near impact, and the split-week evidence does not show clean propagation from early- to late-week liquidity. Predetermined price tests further indicate that the impact reversal is not confined to the lowest-priced stocks, although low nominal price is associated with greater long-horizon persistence.

The paper does not establish that small trades uniformly consume liquidity or that small-trade frequency is a structural shock. Its conclusion is instead a measurement one. Before liquidity

implications are assigned to an observed transaction category, relative transaction frequency and relative trade size should be separated from aggregate trading scale. In this setting, aggregation is not merely imprecise; it reverses the empirical inference.

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A Data construction and descriptive evidence

This appendix provides additional information on sample selection, variable construction, and the distribution of the main variables. Table A.1 reports the sample flow and compares observations retained and excluded at the principal sample-selection steps. Table A.2 defines the trading, liquidity, and control variables and reports their units and CSMAR sources. Table A.3 provides descriptive statistics for the common first-stage sample.

Table A.1: Sample construction and selection

<i>Panel A: Sample flow</i>			
Stage	Stock-weeks	Stocks	Retained (%)
Matched weekly panel	3,129,032	5,486	100.0
Positive decomposition states and predetermined price	2,638,021	5,423	84.3
Predetermined firm controls available	2,605,732	5,306	83.3
Common first-stage sample	1,787,131	5,247	57.1
Strict common sample	1,437,390	5,128	45.9

Table A.1: Sample construction and selection

<i>Panel B: Standardized mean differences</i>		
Characteristic	First-stage minus excluded	Strict sample minus remaining
Quoted spread	-0.206	0.156
Log market value	0.291	0.003
Small-trade value share	-0.214	0.343
Total transaction count	0.495	-0.158
Turnover	-0.261	-0.342

Notes: Panel A reports the successive sample restrictions, with retention measured relative to the matched weekly order-flow and spread panel. Panel B reports standardized mean differences between retained and excluded observations. The first column compares the common first-stage sample with observations excluded from that sample within the matched panel. The second compares the strict common sample with the remaining observations in the common first-stage sample. Each standardized difference is the included-minus-excluded mean divided by the pooled standard deviation.

Table A.2: Variable definitions, units, sources, and related literature

Symbol	Definition	Unit and CSMAR source	Related literature
Spread	Weekly mean of the daily equal-weighted relative quoted spread in equation (10).	Percentage points; individual-stock spread table.	Stoll (1978); Huang and Stoll (1997)
s^V	Small-trade value divided by all active-trade value in the week. Small trades are below RMB 50,000.	Ratio; CSMAR Factor Research Series, daily buy–sell imbalance table.	Hvidkjaer (2008); Lu et al. (2025); Lei et al. (2026)
s^N	Number of active small trades divided by all active trades in the week.	Ratio; CSMAR Factor Research Series, daily buy–sell imbalance table.	Lee and Radhakrishna (2000); Boehmer et al. (2021)
χ^{NC}	Orthonormal log ratio of small to non-small transaction counts.	Unit-free log ratio; transaction-count fields.	Aitchison (1982); Egozcue et al. (2003); Jones et al. (1994); Chan and Fong (2000)
χ^{RS}	Orthonormal log ratio of average small-trade value to average non-small-trade value; equivalently, value composition minus count composition.	Unit-free log ratio; active-trade value and transaction-count fields.	Lin et al. (1995); Huang and Masulis (2003); equation (3)

Symbol	Definition	Unit and CSMAR source	Related literature
x^{TC}	Log total transaction count.	Log transactions; transaction-count fields.	Jones et al. (1994); Dufour and Engle (2000)
x^{AV}	Log average trade value, defined as log total active-trade value minus log total transaction count.	Log RMB per transaction; active-trade value and transaction-count fields.	Chan and Fong (2000); Huang and Masulis (2003); equation (5)
Price	Previous calendar-month closing price used before the innovation week; controls for nominal-threshold classification and proportional tick-size variation.	RMB per share; return files.	Harris (1994); nominal-threshold control
Controls	Log market value, market-to-book, momentum, one-month reversal, turnover, return on assets, and accruals.	Previous-month ratios or logs; trading and financial files.	Firm, return, activity, and fundamental conditions

Notes: The table defines the variables used in the main analysis. Small and non-small trading measures are constructed from active-trade value and transaction-count fields. The four decomposition coordinates require positive value and count observations in both trade-size categories. Predetermined variables are measured before the innovation week. Ask and bid refer to the best quoted prices at a valid intraday quote record.

Table A.3: Descriptive statistics for the common first-stage sample

Variable	N	Mean	SD	P25	Median	P75
Quoted spread	1,787,131	0.1578	0.0908	0.0957	0.1348	0.1933
Small-trade value share (S^V)	1,787,131	0.2697	0.1520	0.1576	0.2554	0.3638
Small-trade count share (S^N)	1,787,131	0.7603	0.1669	0.6947	0.8066	0.8768
Small-trade count composition (x^{NC})	1,787,131	0.9426	0.6925	0.5814	1.0098	1.3876
Relative trade size (x^{RS})	1,787,131	-1.7931	0.2102	-1.9075	-1.7623	-1.6458
Log total transaction count (x^{TC})	1,787,131	8.9963	0.6782	8.6194	9.0949	9.4969
Log average trade value (x^{AV})	1,787,131	10.7080	0.7605	10.1737	10.6169	11.1457
Predetermined price	1,787,131	15.3472	17.9540	6.1100	10.1600	17.6800
Log market value	1,787,131	15.6612	1.0388	14.9252	15.4898	16.2571
Market-to-book	1,787,131	3.1018	2.9571	1.4576	2.2828	3.6501
Momentum	1,787,131	0.0957	0.4116	-0.1745	0.0332	0.2899
Reversal	1,787,131	0.0123	0.1221	-0.0620	0.0010	0.0720
Turnover	1,787,131	0.5015	0.4692	0.2032	0.3616	0.6406
ROA	1,787,131	0.0300	0.0663	0.0094	0.0319	0.0616
Accruals	1,787,131	0.0313	0.0788	0.0015	0.0241	0.0592

Notes: The table reports descriptive statistics for the 1,787,131 stock-weeks in the common first-stage sample. The quoted spread is measured in percentage points and predetermined price in RMB per share. Count composition and relative trade size are orthonormal log-ratio coordinates; total transaction count and average trade value are natural logarithms. Continuous trading variables and firm controls are winsorized at the pooled 1st and 99th percentiles; winsorization caps rather than deletes observations.

B First-stage construction and diagnostics

The baseline design projects each execution state on the same 52-week histories of all four states, predetermined controls, and stock and week fixed effects. This appendix provides additional evidence on that projection. Table B.1 reports the one-week own- and cross-state coefficients and tests whether the full 52-lag history of each predictor contributes jointly to each first-stage equation. We then

examine whether shortening the common first-stage history materially changes the focal count-composition path.

B.1 First-stage construction

Table B.1: Cross-state structure of the common first-stage projections

Predictor	Count composition	Relative size	Total count	Average value
<i>Panel A: Coefficients on the one-week lag</i>				
Count composition	0.5266*** (0.0146)	0.0721*** (0.0043)	0.0305*** (0.0048)	0.0096 (0.0083)
Relative trade size	0.1763*** (0.0115)	0.4682*** (0.0049)	-0.1006*** (0.0063)	-0.0435*** (0.0075)
Total transaction count	0.0525*** (0.0035)	0.0242*** (0.0013)	0.5794*** (0.0048)	-0.0529*** (0.0035)
Average trade value	-0.1687*** (0.0119)	0.1031*** (0.0038)	0.1694*** (0.0044)	0.6891*** (0.0083)
<i>Panel B: Joint p-value for all 52 lags of the predictor</i>				
Count composition	< 0.001	< 0.001	< 0.001	< 0.001
Relative size	< 0.001	< 0.001	< 0.001	< 0.001
Total count	< 0.001	< 0.001	< 0.001	< 0.001
Average value	< 0.001	< 0.001	< 0.001	< 0.001
Observations	1,787,131	1,787,131	1,787,131	1,787,131
Within R^2	0.7432	0.5281	0.7541	0.7059

Notes: Columns correspond to the dependent execution state in equation (11). Panel A reports coefficients on the one-week lag of each row state, with two-way clustered standard errors in parentheses. Panel B reports p-values from joint tests that all 52 lags of the corresponding row state are zero. Every first-stage equation includes the 52-week histories of all four states, predetermined controls, and stock and week fixed effects and is estimated on the common first-stage sample. ***, **, and * denote significance at 1%, 5%, and 10%.

The one-week own-state coefficients range from 0.468 for relative trade size to 0.689 for average trade value, confirming substantial persistence before residualization. Cross-state predictability is also economically meaningful. For example, lagged relative trade size is positively associated with subsequent count composition but negatively associated with total transaction count, while lagged average trade value predicts lower count composition and higher total transaction count. Each 52-lag predictor block is jointly significant in every first-stage equation. Separate univariate filters would therefore leave predictable cross-state variation in the residuals. These coefficients motivate the symmetric first-stage information set; they are predictive rather than structural.

B.2 Alternative first-stage history

The baseline first stage uses 52 weeks of history to remove persistent and cross-state predictable variation. As a sensitivity check, we shorten the common history to 13 weeks while retaining the symmetric four-state information set. The focal estimates change little. Using all available observations at each horizon, the impact coefficient is 0.2661 basis points under the 52-week specification and 0.2677 under the 13-week specification. The corresponding week-13 estimates are 0.0850 and 0.0853, and the week-52 estimates are 0.0211 and 0.0264. The count-composition path is therefore insensitive to whether the common first stage conditions on one year or one quarter of state history.

C Additional timing and stability evidence

C.1 Weekly timing diagnostics

Before imposing the split-week design, we examine whether the weekly data exhibit clean temporal ordering around the count-composition innovation. Table C.1 provides three diagnostics. First, it relates the current quoted spread to future count-composition innovations. Second, it relates the current innovation to prior spread levels. Third, it relates the current innovation to pre-innovation spread changes. The one-week future innovation and several pre-innovation spread changes are significantly associated with the relevant spread outcomes. These patterns indicate short-horizon sorting within weekly observations and motivate the stricter split-week design in Section 5.4. They are timing diagnostics, not evidence that future innovations cause current quotes.

Table C.1: Timing diagnostics for the count-composition innovation

Diagnostic	One week	Four weeks	Thirteen weeks
Future innovation predicting current spread	0.0976*** (0.0135)	0.0028 (0.0092)	-0.0002 (0.0090)
Within R^2	0.8930	0.8922	0.8904
Prior spread level	0.0948*** (0.0136)	-0.0021 (0.0093)	0.0009 (0.0099)
Within R^2	0.8935	0.8917	0.8869
Pre-innovation spread change to (w-1)	0.0849*** (0.0128)	0.1093*** (0.0180)	0.1422*** (0.0277)
Within R^2	0.0180	0.0823	0.1737

Notes: Coefficients and standard errors are in basis points. “Future innovation predicting current spread” regresses the current quoted spread on the count-composition innovation measured at the indicated future horizon. “Prior spread level” regresses the indicated lagged spread on the current innovation. “Pre-innovation spread change” uses the change from the indicated prior horizon to week $w - 1$ as the dependent variable. Each coefficient row is followed by the corresponding within- R^2 . The specifications retain the baseline controls and fixed-effect structure where applicable. These estimates are temporal-ordering diagnostics and are not interpreted causally. *** denotes significance at 1%.

C.2 Split-week serial-dependence sensitivity

Because the split-window residuals retain short-run dependence, we additionally filter the early- and late-window residuals on the common vector of one-week-lagged split residuals. This refinement reduces the lag-one residual coefficients below 0.025 in absolute value. Re-estimating the temporal-ordering exercise yields a forward coefficient of 0.059 basis points for the association between the early count-composition innovation and the late spread. The reverse-timing coefficient remains larger, at 0.089 basis points. The additional filtering therefore changes the magnitude of the forward estimate but not the temporal-ordering conclusion: the split-week evidence continues to locate the association near early-week quote formation without establishing clean directional propagation into the late-window spread.

C.3 Stability across market eras

The pooled sample spans substantial changes in investor participation, execution technology, and market oversight. We therefore re-estimate the four common first-stage projections and the nested

measurement models separately for 2005–2011, 2012–2018, and 2019–2025. Table C.2 shows that M0 and M1 produce negative impact coefficients in every era. The unrestricted M2 count-composition coefficient is statistically indistinguishable from zero in 2005–2011 and positive in the two later periods. The joint equal-loading restrictions are rejected at impact in all three eras. The timing of the unrestricted coefficient varies more substantially across periods. The stable result is therefore the rejection of the aggregation restrictions, not an invariant dynamic coefficient path.

Table C.2: Nested measurement models across market eras

Era	N	M0: (h=0)	M1: (h=0)	M2: (h=0)	M2: (h=1)	M2: (h=13)	M2: (h=52)
2005–2011	129,043	-1.4944*** (0.0862)	-0.8799*** (0.0841)	-0.0196 (0.0729)	0.1355*** (0.0507)	0.0803 (0.0658)	0.0149 (0.0773)
Within R^2 , 2005–2011		0.7632	0.7667	0.7720	0.6492	0.2759	0.0487
2012–2018	203,818	-0.4247*** (0.0405)	-0.1796*** (0.0368)	0.2616*** (0.0321)	0.2502*** (0.0325)	0.2003*** (0.0443)	-0.0916 (0.0582)
Within R^2 , 2012–2018		0.8005	0.8030	0.8064	0.7359	0.4045	0.0771
2019–2025	802,542	-0.4968*** (0.0267)	-0.2411*** (0.0318)	0.2772*** (0.0243)	0.0607** (0.0264)	0.0115 (0.0278)	0.0246 (0.0277)
Within R^2 , 2019–2025		0.8310	0.8327	0.8373	0.7730	0.3781	0.0497

Notes: Coefficients and standard errors are in basis points per era-specific marginal standard deviation. M0 leaves value composition and trading scale aggregated; M1 decomposes value composition only; M2 estimates all four execution margins jointly. Within each era, all four first-stage projections are re-estimated using the common 52-week information set, and all reported specifications use the same observations across the displayed horizons. The within- R^2 rows correspond column by column to the reported model and horizon. The two M2 equal-loading restrictions are jointly rejected at the impact horizon with $p < 0.001$ in every era. *** and ** denote significance at 1% and 5%.