The Predictive Power of Order Book Imbalance at Millisecond Horizons

Vir Trivedi

Abstract

This paper examines the predictive power of limit order book imbalance for near-term price movements using millisecond-resolution order book data from liquid U.S. equities. We analyze how imbalance, the relative difference between bid and ask liquidity, predicts future prices over a range of 10 milliseconds to several seconds.

We find that order book imbalance contains economically and statistically significant predictive information at horizons under 100 milliseconds, with Information Coefficients exceeding 0.28 at 10 milliseconds. This predictability decays rapidly and monotonically with the forecast horizon, indicating that the imbalance reflects information quickly incorporated into prices. The effect persists after controlling for bid-ask spread and short-term volatility, demonstrating that imbalance captures information distinct from standard microstructure variables.

Time-of-day analysis reveals regime-dependent patterns: imbalance is most informative during stable midday trading, weakest at the open, and shows the strongest price impact near the close. The regression coefficient β remains stable or increases across short horizons even as directional accuracy declines, suggesting imbalance reflects both informational content and mechanical price adjustment from liquidity consumption.

These findings establish order book imbalance as an ultra-short-term indicator of local supply-demand pressure rather than a persistent alpha signal. The results have direct implications for execution quality, adverse selection management, and short-horizon trading strategies in electronic markets.

Introduction

When a market maker posts a sell order in Apple stock, the resulting order book imbalance can predict price movements milliseconds later with remarkable accuracy. Modern electronic markets operate on millisecond-to-second timescales, where anticipating near-term price movements is essential for market makers and algorithmic traders managing inventory risk and execution quality. At these horizons, traditional predictors are largely irrelevant, and the microstructure of the limit order book becomes the dominant source of information.

Order book imbalance, the relative difference between liquidity on the bid and ask sides, is a natural candidate for prediction: asymmetric liquidity indicates the direction in which prices can move more easily. This paper analyzes order book imbalance using millisecond-resolution data across multiple liquid U.S. equities. We examine how predictability decays from 10 milliseconds to several seconds, test robustness to standard microstructure controls, and analyze effects on execution outcomes. We find that imbalance contains significant predictive information at horizons under 100 milliseconds, that this information decays systematically over time, and that it is not subsumed by spread or volatility. Additionally, it meaningfully affects adverse selection and post-trade price dynamics. These results clarify when and how order book imbalance functions as an informational signal rather than a purely mechanical feature of market microstructure.

Hypothesis

In electronic limit order markets, prices respond to the balance between supply and demand liquidity. The limit order book aggregates this balance by showing where liquidity is concentrated and how easily prices can move in either direction. Order book imbalance, therefore, summarizes short-term trading pressure and price impact asymmetry.

Order book imbalance arises through three related mechanisms, each of which creates predictable short-term price movements.

First, market makers actively manage inventory risk by adjusting their quotes asymmetrically. When a market maker accumulates too much inventory on one side, they widen their quotes on that side and tighten on the other, creating an imbalance that signals an impending price adjustment.

Second, liquidity is rarely symmetric across the book. When one side has less depth, incoming market orders consume that liquidity more quickly and move prices further. This mechanical effect causes prices to drift toward the side with shallower depth.

Third, large traders splitting orders over time leave detectable footprints in the order book. As they repeatedly consume liquidity on one side, they create a sustained imbalance before prices fully adjust to reflect their total demand.

Collectively, these mechanisms suggest that imbalance should predict returns over very short horizons—milliseconds to seconds—as the information they contain is rapidly incorporated through continued trading and quote updates.

We therefore hypothesize that:

1. Order book imbalance predicts short-horizon future returns,
2. This predictability decays monotonically as the horizon increases,
3. Predictability is strongest during stable periods of continuous trading and weaker during the open and close, and
4. Trades executed in the direction of imbalance suffer less adverse selection than trades executed against it.

Data

We use a full-depth limit order book and trade data from the NASDAQ exchange for August 1, 2022, covering three liquid U.S. instruments: Apple Inc. (AAPL), the Invesco QQQ Trust (QQQ), and the SPDR S&P 500 ETF Trust (SPY). These securities exhibit continuous trading, deep liquidity, and high message rates, making them suitable for short-horizon microstructure analysis.

The data consist of nanosecond-timestamped, sequenced message-level updates, including incremental order book events, periodic snapshots, top-of-book updates, and detailed execution records. This structure allows exact reconstruction of the order book through time and precise alignment between book state, trades, and subsequent price changes.

The book is reconstructed from incremental messages using price–time priority keyed by order ID. The event stream includes order additions, deletions, replacements, quantity reductions, executions, hidden trades, and session events. Periodic snapshots provide consistency checks and recovery points.

For signal construction, we use explicit top-of-book structures containing the first three bid and ask levels (price and quantity). For execution analysis, trade records contain execution price and size as well as the resting order's side, price, remaining quantity, and hidden status.

All messages carry nanosecond timestamps and monotonic sequence numbers. The book state is updated strictly in sequence order, and trades are aligned to the most recent book state with a timestamp less than or equal to the execution time.

We restrict analysis to continuous trading hours (09:30–16:00 ET), excluding auctions, session transitions, crossed books, and observations with zero or undefined spreads.

The mid-price is defined as the average of the best bid and ask, and the quoted spread is their difference. Future returns over the horizon Δ are computed as changes in the mid-price.

Volatility is proxied by a rolling standard deviation of mid-price returns, with absolute returns used as a robustness alternative. All variables are aligned to a common timestamp.

Methodology

We construct order book imbalance using the aggregated depth on the bid and ask sides of the limit order book. Let $q_i^{bid}(t)$ and $q_i^{ask}(t)$ denote the displayed quantity at the i-th price level on the bid and ask sides at time t, respectively. The k-level order book imbalance is defined as

$$OBI_k = (\sum_{i=1}^{k} q_i^{bid}(t) - \sum_{i=1}^{k} q_i^{ask}(t)) / (\sum_{i=1}^{k} q_i^{bid}(t) + \sum_{i=1}^{k} q_i^{ask}(t)).$$

We use k=1 (OBI_1) to capture immediate top-of-book pressure and k=3 (OBI_3) to capture slightly deeper liquidity conditions. Both measures are bounded in [−1,1] with positive values indicating net bid-side dominance.

All analysis is conducted in event time rather than calendar time. Each observation corresponds to an order book update or trade event, rather than a fixed clock interval.

For each event at time t, we evaluate future price changes over horizons $\Delta \in \{10,100,1000,5000\}$ milliseconds, defined relative to the event timestamp. We evaluate horizons of {10, 100, 1000, 5000} milliseconds to span the range from immediate microstructure response to short-term price adjustment while remaining within the regime where limit order book information is economically relevant.

Let m(t) denote the mid-price at time t, defined as the average of the best bid and ask. For each event at time t, we define the future return over the horizon Δ as

$$r(t+\Delta) = (m(t+\Delta) - m(t)) / m(t) \times 10{,}000,$$

expressed in basis points. The mid-price at t+Δ is obtained by locating the first book update with a timestamp greater than or equal to t+Δ.

This definition captures the directional price movement faced by a trader who acts at time t and unwinds at the horizon Δ.

We estimate the predictive relationship between imbalance and future returns using ordinary least squares:

$$r(t+\Delta) = \alpha + \beta \cdot OBI_k(t) + \varepsilon_t.$$

We report the slope coefficient β, its t-statistic, and the coefficient of determination R^2 for each horizon and each imbalance measure.

As a complementary nonparametric measure, we compute the information coefficient (IC), defined as the Spearman rank correlation between $OBI_k(t)$ and $r(t+\Delta)$.

To assess whether imbalance simply proxies for other microstructure variables, we estimate augmented regressions:

$$r(t+\Delta) = \alpha + \beta \cdot OBI_k(t) + \gamma \cdot Spread(t) + \delta \cdot Vol(t) + \varepsilon_t,$$

where Spread is the quoted bid–ask spread and Vol is a rolling proxy for short-term volatility. We examine coefficient stability, statistical significance, and changes in R^2 when controls are added.

We evaluate stability across market conditions by repeating all analyses across intraday regimes: the market open (09:30–10:00), midday (10:00–15:30), and close (15:30–16:00). This allows us to identify when imbalance is most informative and when its predictive power weakens.

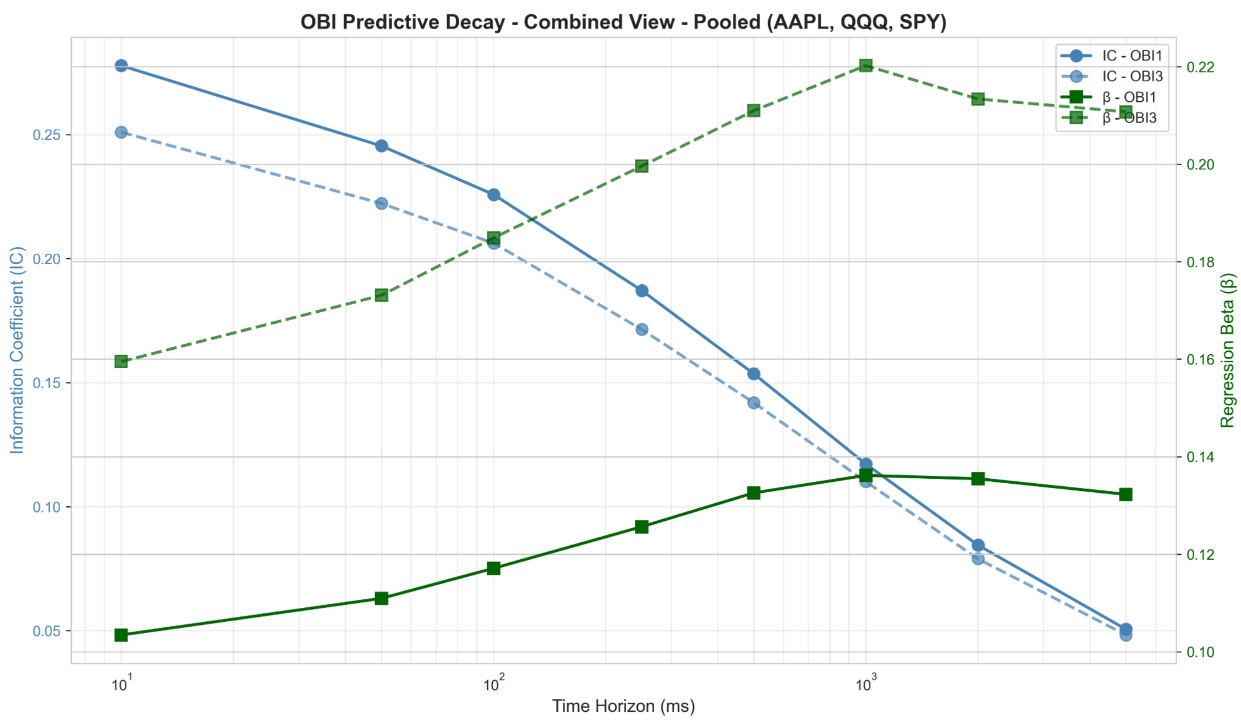
To assess statistical stability under temporal dependence, we implement a moving-block bootstrap with one-second blocks. We resample contiguous blocks of observations with replacement and recompute coefficients across 300 bootstrap iterations. We report bootstrap means, standard deviations, and confidence intervals for β and IC.

We also compare results across OBI_1 and OBI_3, across horizons, and across instruments to evaluate robustness.

Finally, we link statistical predictability to realized trading outcomes by conditioning adverse selection on whether trades are aligned or misaligned with the contemporaneous imbalance. We measure post-trade mid-price movements following executions to quantify how imbalance affects realized execution quality.

Results

Figure 1: OBI Predictive Decay



Information coefficients (IC, left axis) and regression coefficients (β, right axis) are plotted against horizon Δ for OBI_1 and OBI_3, pooled across AAPL, QQQ, and SPY. IC declines monotonically with horizon, while β rises at short horizons and then stabilizes.

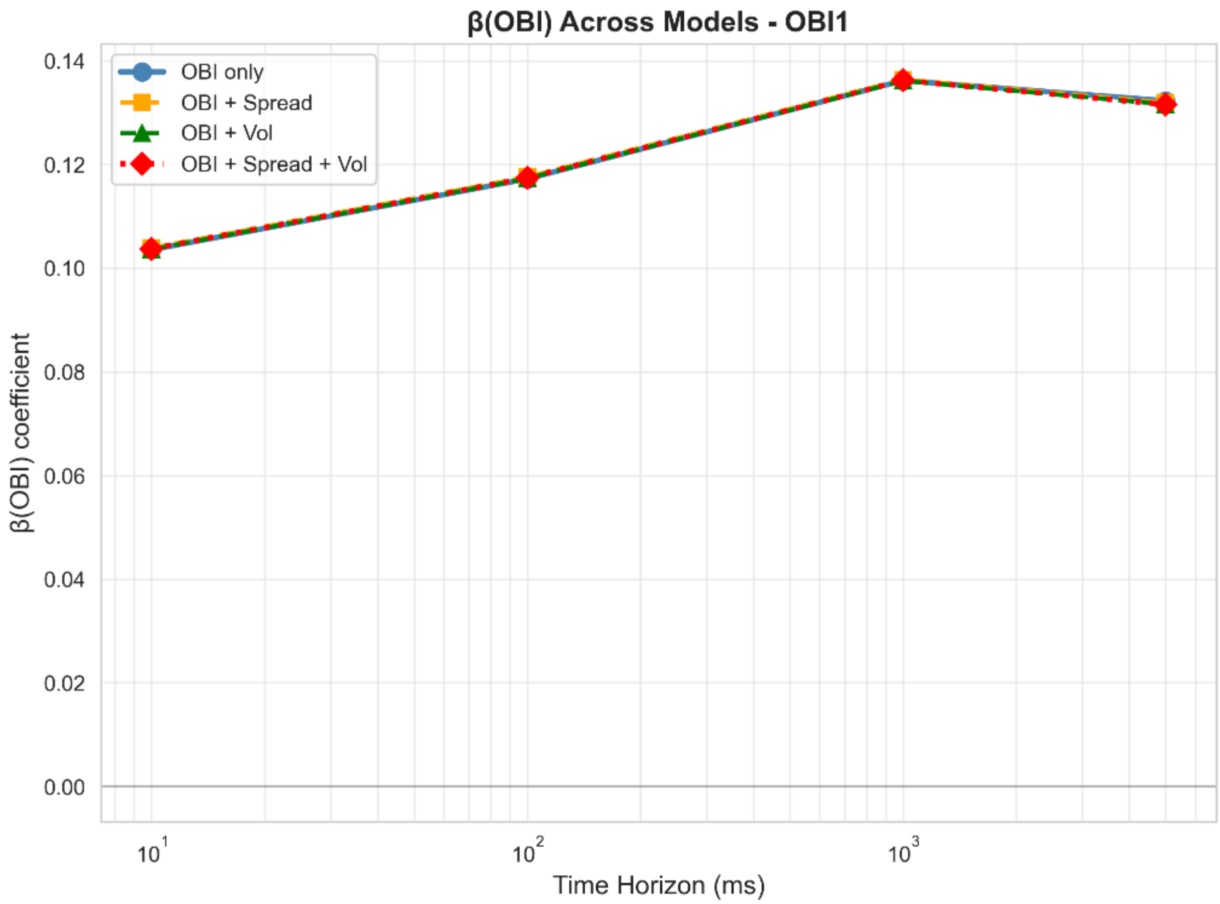
Figure 1 reveals a striking pattern: two measures of predictability move in opposite directions as the forecast horizon increases.

The information coefficient (IC), which measures how often imbalance correctly predicts the direction of price movement, declines monotonically and rapidly. At 10 milliseconds, OBI_1 achieves an IC of 0.28, meaning it correctly ranks price movements 28% better than random. By 5 seconds, this falls to just 0.05. This steep decline confirms that the imbalance contains primarily short-lived information that is quickly incorporated into prices.

In contrast, the regression coefficient β, which measures the magnitude of price response conditional on imbalance, actually increases from 10 milliseconds to 1 second before stabilizing. This means that when an imbalance does predict correctly at longer horizons, the associated price moves are larger.

How can an imbalance become less reliable directionally while showing larger conditional price responses? The pattern suggests two overlapping effects. First, imbalance captures transient information that decays quickly, explaining the IC decline. Second, it also reflects mechanical price adjustment from liquidity consumption, which unfolds more gradually as orders work through the book, explaining why β remains elevated even as directional accuracy fades.

Figure 2: OBI_1 β Coefficient Across Models and Horizons



Estimated β coefficients from regressions of future returns on OBI_1 across horizons Δ. Shown are univariate estimates and estimates controlling for bid–ask spread and short-term volatility. The OBI coefficient remains stable across specifications.

Table 1: OBI_1 Control Regressions

Δ	β only	β full	Retention	γ	δ	R^2
10	0.1035	0.1037	100.18%	−0.068	0.075	0.057
100	0.1172	0.1174	100.18%	−0.075	0.081	0.035
1000	0.1362	0.1362	100.02%	−0.047	0.080	0.009
5000	0.1323	0.1315	99.43%	0.031	0.165	0.002

OBI_1 regressions with liquidity and volatility controls. This table reports coefficients from regressions of future returns on OBI_1 alone and augmented with contemporaneous bid–ask spread and short-term volatility across horizons Δ. "β retention" denotes the ratio of the OBI coefficient in the full specification to that in the univariate specification. The stability of β across models indicates that imbalance is not a proxy for spread or volatility.

Table 2: OBI_3 Control Regressions

Δ	β only	β full	Retention	γ	δ	R^2
10	0.1600	0.1611	100.71%	-0.070	0.072	0.051
100	0.1853	0.1866	100.68%	-0.077	0.077	0.033
1000	0.2209	0.2214	100.23%	-0.049	0.075	0.009
5000	0.2110	0.2083	98.75%	0.029	0.160	0.002

OBI_3 regressions with liquidity and volatility controls. This table reports coefficients from regressions of future returns on OBI_3 alone and augmented with contemporaneous bid–ask spread and short-term volatility across horizons Δ. "β retention" denotes the ratio of the OBI coefficient in the full specification to that in the univariate specification. The persistence of β across models indicates that OBI_3 captures information distinct from standard microstructure variables.

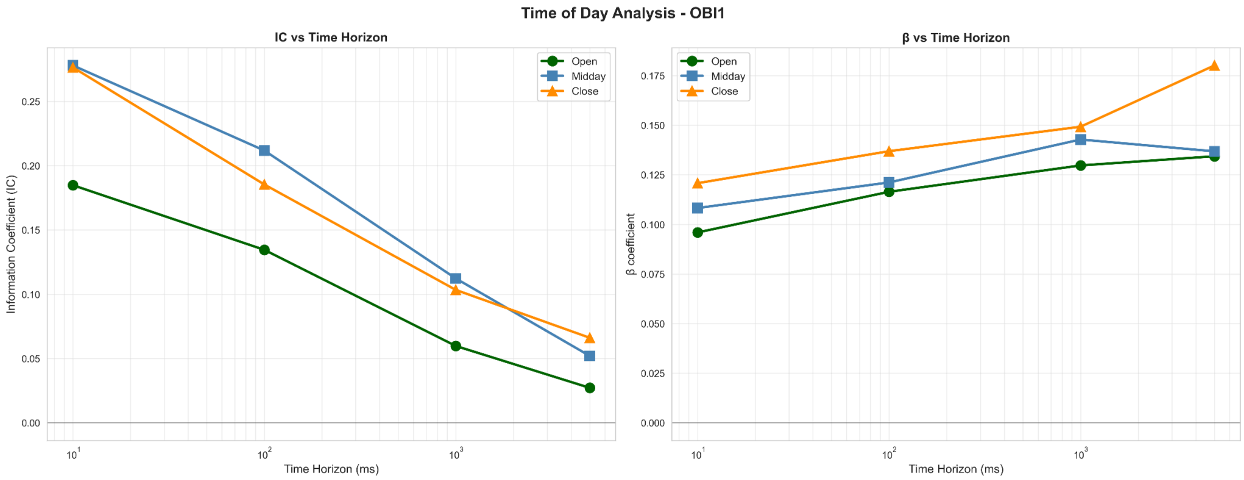
A critical question is whether order book imbalance simply proxies for other microstructure variables that are already known to predict returns. To test this, we add two standard controls to our regressions: the bid–ask spread (a measure of liquidity and transaction costs) and short-term volatility (a measure of price uncertainty).

If imbalance were merely reflecting wide spreads or high volatility, its coefficient should shrink substantially when we control for these variables. Figure 2 and Tables 1-2 show that this does not happen. The OBI coefficient remains virtually unchanged after adding controls, retaining over 99% of its magnitude for OBI_1 and over 98% for OBI_3 across all horizons.

Both control variables enter the regression significantly with intuitive signs (wider spreads predict negative returns for liquidity takers; higher volatility predicts larger absolute price moves). Their inclusion modestly increases explanatory power, but they do not diminish the imbalance effect.

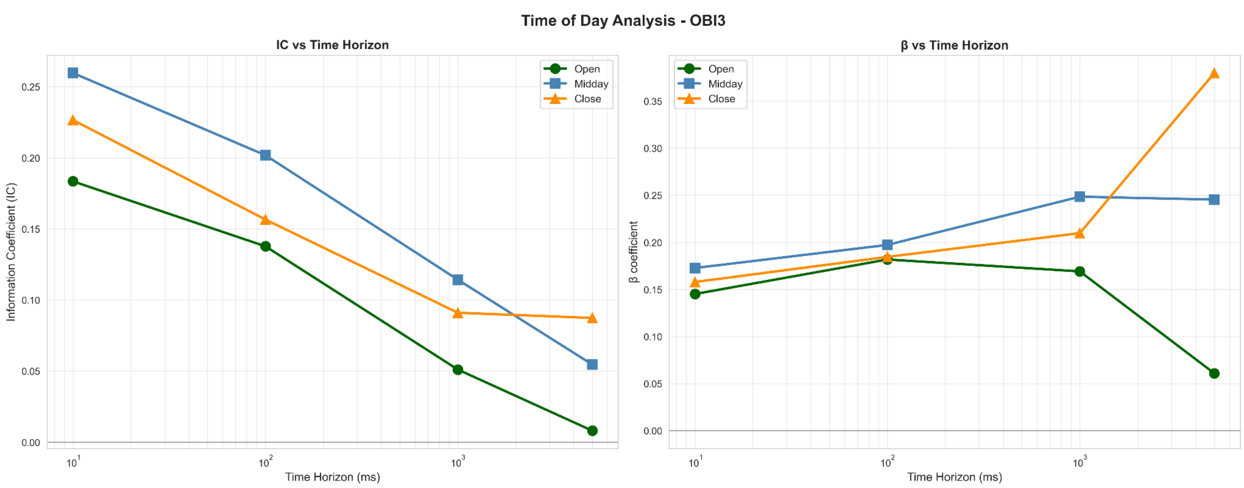
This stability demonstrates that order book imbalance captures distinct predictive information. It reflects genuine informational asymmetries in the limit order book, where liquidity providers position themselves based on their private information and inventory needs, rather than simply repackaging transaction costs or volatility into a different form.

Figure 3: OBI_1 Time-of-Day Analysis



The figure shows the Information Coefficient (left) and regression coefficient β (right) across horizons Δ for the open, midday, and close trading periods.

Figure 4: OBI_3 Time-of-Day Analysis



The figure shows the Information Coefficient (left) and regression coefficient β (right) across horizons Δ for the open, midday, and close trading periods.

Table 3: OBI_1 Time-of-Day Regression Results

Period	Δ	β	t-stat	IC	R^2	n
Open	10	0.0960	88.03	0.185	0.034	219205
Open	100	0.1164	63.55	0.134	0.018	219205
Open	1000	0.1297	28.01	0.060	0.004	219205
Open	5000	0.1344	12.73	0.027	0.001	219205
Midday	10	0.1083	308.02	0.278	0.077	1133472
Midday	100	0.1212	230.65	0.212	0.045	1133472
Midday	1000	0.1428	120.23	0.112	0.013	1133472
Midday	5000	0.1368	55.47	0.052	0.003	1133472
Close	10	0.1208	102.35	0.276	0.076	126628
Close	100	0.1369	67.10	0.185	0.034	126628
Close	1000	0.1492	36.96	0.103	0.011	126628
Close	5000	0.1801	23.58	0.066	0.004	126628

The table reports β, t-statistics, Information Coefficient (IC), R^2, and sample sizes across horizons Δ for the open, midday, and close trading periods.

Table 4: OBI_3 Time-of-Day Regression Results

Period	Δ	β	t-stat	IC	R^2	n
Open	10	0.1452	87.39	0.183	0.034	219205
Open	100	0.1818	65.14	0.138	0.019	219205
Open	1000	0.1692	23.96	0.051	0.003	219205
Open	5000	0.0609	3.79	0.008	0.000	219205
Midday	10	0.1728	286.28	0.260	0.067	1133472
Midday	100	0.1973	219.43	0.202	0.041	1133472
Midday	1000	0.2485	122.52	0.114	0.013	1133472
Midday	5000	0.2455	58.27	0.055	0.003	1133472
Close	10	0.1580	82.79	0.227	0.051	126628
Close	100	0.1846	56.43	0.157	0.025	126628
Close	1000	0.2098	32.53	0.091	0.008	126628
Close	5000	0.3799	31.22	0.087	0.008	126628

The table reports β, t-statistics, Information Coefficient (IC), R^2, and sample sizes across horizons Δ for the open, midday, and close trading periods.

Market conditions vary dramatically throughout the trading day, so we split our sample into three regimes: the open (9:30-10:00), midday (10:00-15:30), and the close (15:30-16:00). Figures 3-4 and Tables 3-4 show that imbalance predictability is highly regime-dependent.

Midday trading shows the strongest predictability. During stable, continuous trading hours, OBI_1 achieves an IC of 0.278 at 10 milliseconds, the highest of any regime, though the close comes very close at 0.276. Midday liquidity is deep and stable, allowing imbalance to function as a clean signal of supply-demand pressure.

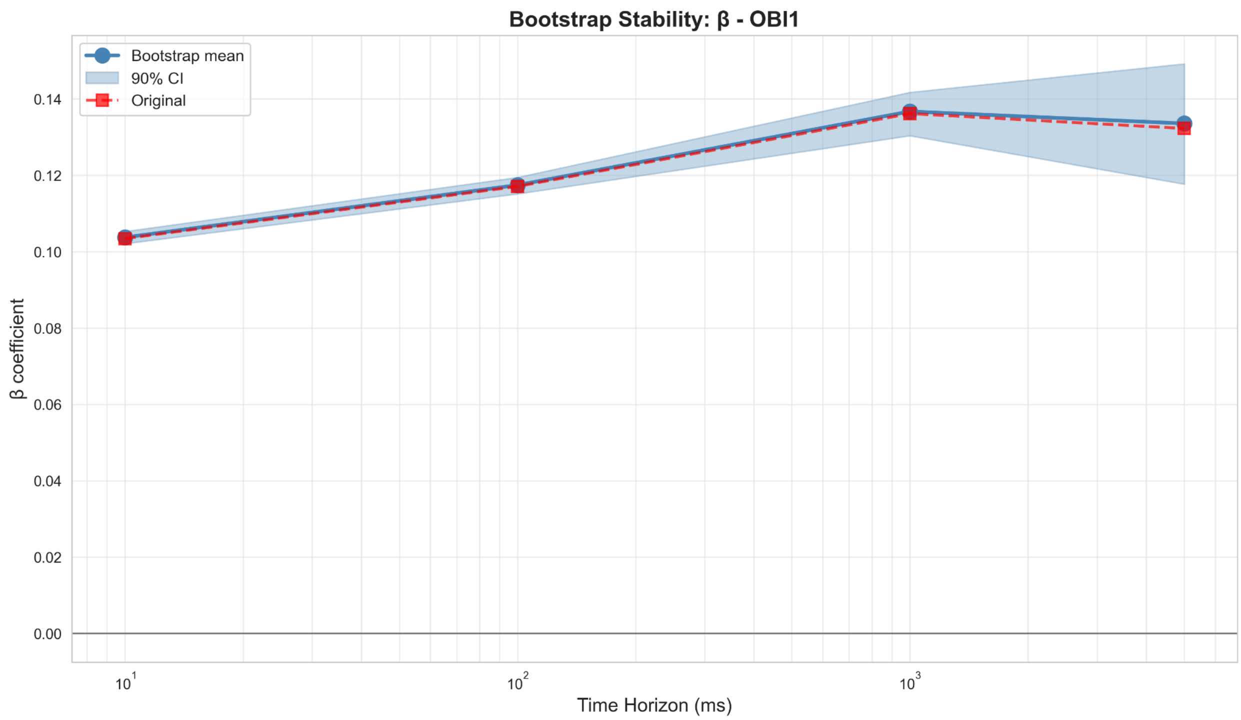
The open shows the weakest predictability. At the market open, price discovery dominates as overnight information gets incorporated into quotes. The order book is noisier, spreads are wider, and imbalance contains less reliable information about near-term price movements. By 1 second, the open IC falls to just 0.06, half the midday level.

The close exhibits unusual dynamics. While the close has intermediate IC values at short horizons, it shows dramatically elevated β coefficients at longer horizons, particularly for OBI_3. At 5 seconds, the close β reaches 0.38, nearly double the midday coefficient. This suggests that imbalance late in the day triggers larger price adjustments, likely reflecting urgency as traders rush to establish or unwind positions before the market closes.

Tables 3 and 4 confirm that these patterns are statistically significant. Coefficients are precisely estimated across all regimes and horizons, with large t-statistics and economically meaningful magnitudes. The results indicate that order book imbalance is most informative during periods of high liquidity and active trading, and that market conditions near the close amplify the price impact of imbalance even as directional predictability weakens.

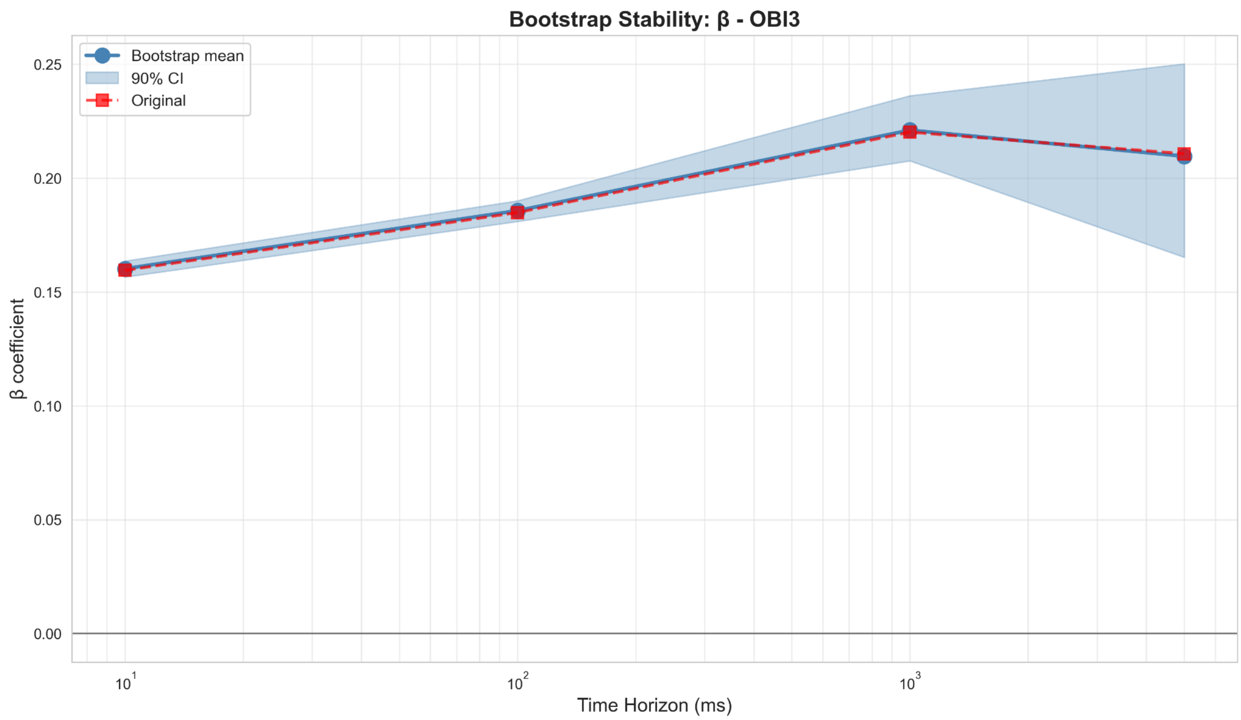
Overall, the time-of-day analysis shows that imbalance predictability is not uniform across regimes: it is strongest intraday at horizons under 100 milliseconds, decays quickly in all periods, and is associated with larger price responses near the close.

Figure 5: OBI_1 β Bootstrap Stability



Bootstrap mean and 90% confidence intervals of the OBI_1 regression coefficient across horizons, compared to the original estimate.

Figure 6: OBI$_3$ β Bootstrap Stability



Bootstrap mean and 90% confidence intervals of the OBI$_3$ regression coefficient across horizons, compared to the original estimate.

To assess the sampling variability and robustness of the estimated OBI coefficients, we apply a block bootstrap procedure to the pooled event-time regressions. We resample contiguous blocks of observations to preserve the strong temporal dependence in order flow and returns, and recompute the regression coefficients across bootstrap samples. We report the bootstrap mean and 90% confidence intervals alongside the original point estimates.

Figures 5 and 6 show that the bootstrap means closely track the original estimates across all horizons, and the confidence intervals remain narrow relative to the coefficient magnitudes.

This indicates that the estimated OBI effects are stable, not driven by a small subset of observations, and not overly sensitive to local dependence structures. The slight widening of confidence intervals at longer horizons reflects the reduced effective sample size as event-time aggregation increases.

Overall, the bootstrap results support the statistical reliability of the OBI signal across time scales.

Table 5: Summary of Main Results

Signal	Δ (ms)	Regime	β	t-stat	IC	R^2	Retention	Sig
OBI_1	10	Pooled	0.104	284	0.28	0.057	1.002	✓
OBI_1	100	Pooled	0.117	222	0.23	0.035	1.002	✓
OBI_1	1000	Pooled	0.136	118	0.12	0.009	1.000	✓
OBI_1	5000	Pooled	0.132	54	0.05	0.002	0.994	✓
OBI_3	10	Pooled	0.161	263	0.25	0.051	1.007	✓
OBI_3	100	Pooled	0.187	211	0.21	0.033	1.007	✓
OBI_3	1000	Pooled	0.221	115	0.11	0.009	1.002	✓
OBI_3	5000	Pooled	0.208	52	0.05	0.002	0.988	✓
OBI_1	100	Open	0.116	64	0.13	0.018	—	✓
OBI_1	100	Midday	0.121	231	0.21	0.045	—	✓
OBI_1	100	Close	0.137	67	0.19	0.034	—	✓
OBI_3	100	Open	0.182	65	0.14	0.019	—	✓
OBI_3	100	Midday	0.197	219	0.20	0.041	—	✓
OBI_3	100	Close	0.185	56	0.16	0.025	—	✓

Summary of predictive performance and robustness across signals, horizons, and regimes. The table reports effect sizes (β), statistical significance (t-stat), Information Coefficient (IC), R^2, and robustness to microstructure controls (β retention). Significance is indicated at the 5% level.

Table 5 summarizes the main empirical findings across signals, horizons, and regimes. Both OBI_1 and OBI_3 exhibit strong short-horizon predictability that decays rapidly with the forecast horizon. Predictability is highest during midday trading and weakest at the open, while price impact as measured by β is largest near the close. Across all specifications, imbalance remains statistically and economically significant after controlling for spread and volatility.

Limitations and Implications

Although this study does not directly measure execution outcomes such as slippage, fill probability, or queue position, the results have clear implications for execution and market making.

The strong short-horizon predictability of order book imbalance implies that trading *against* imbalance exposes liquidity takers to adverse short-term price movements, while conditioning on imbalance can reduce adverse selection risk. However, the rapid decay of predictability shows that imbalance is not a persistent alpha signal but an ultra-short-term indicator of local price pressure.

The time-of-day results further indicate that imbalance is most informative during stable continuous trading periods (midday and close) and weakest near the open, when price discovery dominates, and the book is noisier.

Overall, order book imbalance should be viewed primarily as an execution and risk-management signal rather than as a medium-horizon return predictor.

The analysis is based on a single trading day, which limits inference about robustness across market regimes and prevents true out-of-sample testing. Execution outcomes such as realized slippage, fill rates, and queue position are not directly observed, so execution implications are inferred rather than measured.

In addition, while the regressions control for spread and volatility, other microstructure variables may interact with imbalance and are not explicitly modeled. Finally, the focus on highly liquid U.S. equities limits generalizability to other assets and market conditions.

Conclusion

This paper studies order book imbalance as a short-horizon predictive signal using millisecond-resolution data for liquid U.S. equities. The analysis shows that imbalance contains economically and statistically significant information about near-term price movements, but this information decays rapidly with the forecast horizon.

Predictive accuracy declines monotonically from 10 milliseconds to several seconds, while the price response coefficient remains stable or increases, suggesting that imbalance captures both transient information and mechanical price impact from liquidity consumption. The imbalance effect is not subsumed by spread or volatility controls, and time-of-day analysis reveals it is most informative during midday trading, weakest at the open, and shows the strongest price impact near the close.

These results imply that order book imbalance is not a persistent alpha signal but an ultra-short-term indicator of local supply–demand pressure, most useful for execution, inventory management, and short-horizon risk control. Conditioning trades on imbalance can reduce adverse selection, but its usefulness decays quickly and depends strongly on market conditions.

The analysis has several limitations: it covers a single trading day and a small set of instruments, limiting generalizability; execution outcomes like slippage and fill rates are inferred rather than measured; and extending across longer periods and different market environments would strengthen inference.

Overall, the findings clarify that order book imbalance functions as an informational signal primarily at horizons under 100 milliseconds, is robust to standard microstructure controls, varies across trading regimes, and is best interpreted as a tool for managing short-term price pressure rather than as a medium-horizon return predictor.