Financial Engineering and Risk Management (2026)
Clausius Scientific Press, Canada

DOI: 10.23977/ferm.2026.090117
ISSN 2523-2576 Vol. 9 Num. 1

A Study on the Relationship between Limit Order Book Depth and Price Impact in the U.S. Stock Market

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Keywords: U.S. stock market; Limit order book depth; Price impact; Market liquidity; Transaction cost

Abstract: The trading mechanism of the U.S. stock market is becoming increasingly complex. Limit order book depth, as an important indicator of market liquidity, has a significant bearing on the price impact generated in stock trading. Taking the U.S. stock market as the research object, this paper examines the relationship between limit order book depth and price impact, analyzes the distribution and dynamic characteristics of order book depth, explores the internal mechanism through which depth influences price impact, and tests the relationship and its heterogeneity by constructing a panel model with stock and time fixed effects. On this basis, optimization suggestions are proposed with respect to enhancing order book depth, optimizing order allocation, improving dynamic monitoring, and refining execution strategies, so as to provide references for reducing trading costs, improving market liquidity, and raising trading efficiency.

1. Introduction

The U.S. stock market is characterized by a large trading scale, diverse participants, decentralized trading venues, and a high degree of electronification. The limit order book plays an important role in stock trading and in price formation. With the development of high-frequency trading, algorithmic trading, and multiple trading platforms, the submission, cancellation, and execution of orders have continuously accelerated; the structure of the order book has become strongly dynamic; and market liquidity now faces more complex variation. When a large transaction is executed, factors such as order size, the number of limit orders resting on the book, and the distribution of liquidity on the buy and sell sides jointly affect the transaction price, which makes price impact an important indicator of both trade execution quality and the operational efficiency of the market. A close examination of the relationship between limit order book depth and price impact therefore helps to clarify the operating laws of market microstructure in an electronic trading environment.

The question is practically as well as theoretically relevant. Institutional investors who need to liquidate or accumulate large positions face a trade-off between execution speed and execution cost, and the depth of the book at the moment of submission determines how much of that cost is unavoidable. Exchanges, in turn, design maker incentives and liquidity metrics partly on the assumption that deeper books produce smaller price responses. Whether that assumption holds, and

whether it holds uniformly across stocks and trading environments, is an empirical question that the present paper addresses.

2. Theoretical Basis of Limit Order Book Depth and Price Impact

(1) Structure and Operating Mechanism of the Limit Order Book

The limit order book is the core carrier that records buy and sell limit order information in the stock trading market. It consists mainly of buy orders and sell orders: buy orders are arranged from high to low in price, and sell orders from low to high. The best bid and the best ask jointly form the real-time spread. After investors submit limit orders, the system ranks and matches them according to rules such as price-time priority; when a new order satisfies the execution conditions, the trading system matches it automatically, and the unexecuted part remains in the order book [1]. The addition, cancellation, and execution of orders jointly drive the continuous change of the order book structure.

Two features of this mechanism matter for the analysis that follows. First, the book is a queue: a limit order confers priority rather than an immediate transaction, so the quantity resting at each price level is a stock of standing commitments rather than a flow of realized trades. Second, the book is continuously revisable: liquidity providers can cancel and re-submit at negligible cost, so the depth observed at any instant reflects both the willingness to supply liquidity and the expectation of adverse selection. These features imply that depth is informative about the cost of immediacy, but only conditional on the state of the market.

(2) Connotation and Measurement Methods of Order Book Depth

Order book depth refers to the quantity or value of orders on the buy and sell sides within a specific price range, and it reflects the market's ability to absorb trading demand at various price levels. The greater the depth, the more readily the market can absorb large buy or sell orders without pronounced changes in quotes. When measuring depth, indicators such as the number of orders at the best bid and ask, the cumulative order quantity of the top five or top ten price levels, and the cumulative order amount within a given basis point range can be used [2]. Cumulative depth over multiple price levels is particularly informative, because it reflects the distribution of liquidity across price strata and therefore the shape of the effective supply curve facing an incoming order.

Measurement choices are not neutral. A count-based measure treats each order equally and is sensitive to order fragmentation, which algorithmic traders manipulate deliberately; an amount-based measure weights by value and is closer to the object that constrains an execution algorithm; a basis-point measure normalizes across stocks with different price levels. The empirical section below therefore reports results based on the cumulative amount at the top five levels and uses the cumulative count at the top ten levels as a robustness alternative.

(3) Formation Mechanism and Measurement Indicators of Price Impact

Price impact refers to the change in stock price caused by trading orders entering the market, and it is closely related to order size, market liquidity, and the distribution of buying and selling power. When investors submit large active buy orders, the orders may consume sell orders progressively at successive price levels and push the transaction price upward; active sell orders have the opposite effect. Price impact is conventionally divided into a temporary and a permanent component: the former arises mainly from short-term liquidity consumption and is expected to decay as liquidity is replenished, whereas the latter reflects the effect of trading information on market valuation and persists. Common measurement indicators include the price change per unit of volume traded, the price response coefficient, and the deviation between the actual transaction price and a pre-trade benchmark price.

The distinction between the two components is central to the interpretation of the estimates reported later. A negative coefficient of depth on total price impact is consistent with either a reduction in the temporary component, because a deeper book absorbs the same order with fewer price levels consumed, or a reduction in the permanent component, because deeper books signal lower adverse selection. Separating the two requires the decay profile of the impact, which is beyond the scope of the present data; the paper therefore interprets its estimates as the effect of depth on total impact and notes the ambiguity explicitly.

(4) Mechanism by Which Order Book Depth Influences Price Impact

Price impact in the U.S. stock market varies with macroeconomic conditions, market volatility, and trading activity. The macroeconomy is a key factor influencing stock market trends, and it affects stock prices through channels such as corporate profit expectations, investor confidence, and the supply and demand of market funds. When the economy performs well, expectations regarding corporate operations improve, trading demand may increase, and order book depth adjusts with changes in liquidity supply; when the economy is sluggish or uncertainty rises, investor risk appetite may decline and some liquidity providers may withdraw their orders, so that order book depth shrinks and large trades become more likely to trigger significant price impact [3]. Major economic data releases and sharp market fluctuations may further exacerbate imbalances between order supply and demand, which is why the magnitude and duration of price impact differ across trading environments.

Three mechanisms connect depth to impact. The first is mechanical: a given market order walks the book until it is filled, so the number of price levels consumed, and hence the immediate price change, is a decreasing function of the quantity resting at and near the best quotes. The second is informational: the depth of the book is a signal about the private information held by liquidity providers, so a thin book raises the probability that a trade is information-driven and increases the permanent component of impact. The third is strategic: liquidity providers who anticipate large incoming orders widen their quotes or reduce size, which means that observed depth and expected impact are jointly determined. The third mechanism is the source of the endogeneity problem discussed in the empirical design.

3. Characteristic Analysis of Order Book Depth and Price Impact in the U.S. Stock Market

(1) Market Distribution Characteristics of Order Book Depth

Order book depth differs markedly across stocks in the U.S. stock market and is mainly affected by factors such as market capitalization, trading activity, and investor participation. Large-cap stocks generally attract greater market attention and trade more frequently, and they display relatively ample limit orders on both the buy and sell sides; mid- and small-cap stocks are more likely to be influenced by concentrated trading demand and limited liquidity supply, and consequently exhibit shallower order book depth [4]. The distribution of buy and sell orders for the same stock may also be asymmetric, which reflects the imbalance of supply and demand forces in the market.

The cross-sectional pattern has a further implication for estimation. Because depth and market capitalization are strongly correlated, and because capitalization also affects the price elasticity of demand, a specification that omits size would attribute to depth an effect that partly belongs to size. Market capitalization is therefore included among the control variables, and the heterogeneity analysis in Section 3(4) re-estimates the relationship separately for large-cap and smaller-cap groups.

(2) Dynamic Characteristics of Order Book Depth

Order book depth in the U.S. stock market is highly time-varying and is closely related to trading

sessions, market information, and investor order behavior. Within a normal trading day, concentrated trading demand accompanies the opening and closing sessions and causes significant fluctuation in depth, whereas during relatively stable intraday periods the number of resting orders exhibits a degree of stability. When earnings reports, macroeconomic data, or major market events occur, investors may concentrate on adjusting quotes or canceling orders, which causes rapid contraction or redistribution of depth and reflects the sensitivity of liquidity supply to external information [5].

This intraday seasonality is a source of confounding variation. Opening and closing auctions, the intraday pattern of algorithmic execution, and the timing of macro announcements all shift depth and impact simultaneously, so comparisons across stocks are only meaningful when the time dimension is held fixed. The panel specification addresses this by including time fixed effects, which absorb any shock that is common to all stocks on a given day, including announcement effects and market-wide liquidity fluctuations.

(3) Market Performance Characteristics of Price Impact

Price impact in the U.S. stock market is manifested mainly as deviations of transaction prices from pre-trade benchmark prices, widened bid-ask spreads, and intensified short-term price volatility. The effect of an order on price depends on its size and direction: large active orders generally consume several price levels and are therefore more likely to move the transaction price. Price impact also differs in persistence; some impacts weaken as subsequent orders replenish the book and liquidity recovers, while others continue to affect prices because new information enters the market, which reflects the joint operation of liquidity and informational factors.

(4) Differences in Price Impact Under Different Trading Environments

Price impact in the U.S. stock market varies with market volatility, trading activity, and changes in the information environment. When the market is stable and trading continuity is strong, order supply is relatively sufficient and trading demand is generally absorbed promptly, which limits impact. When the market experiences sharp volatility, major disclosures, or sudden events, investors may adjust their strategies, some liquidity providers withdraw orders, and depth thins, which intensifies the price effect of large trades [6]. The magnitude and duration of impact may also differ between high-volatility and low-volatility stocks.

The environment-dependence of impact is the reason the empirical design does not stop at a single average coefficient. If depth and impact co-move differently across volatility states, an unconditional estimate averages over regimes with different slopes and describes none of them, which is why the heterogeneity tests below separate high- and low-volatility subsamples.

4. Empirical Analysis of the Influence of Order Book Depth on Price Impact in the U.S. Stock Market

(1) Sample Selection and Data Sources

The empirical sample selects listed companies in the U.S. stock market with relatively high market attention and trading activity, covering industries such as technology, finance, pharmaceuticals, and consumer products. Representative stocks including Apple, Nvidia, Microsoft, Alphabet, Amazon, and Tesla are chosen as the research objects. Basic stock information and market quotes are obtained from the U.S. stock market data center of Eastmoney, including stock codes, latest prices, market capitalization, and price changes. It should be noted that order book depth and price impact are high-frequency microstructure indicators that cannot be measured from daily data alone; transaction-level records and limit order book snapshots from trading venues such as Nasdaq and the NYSE are required in order to construct stock-day observations.

The panel is therefore built in two layers. The venue layer supplies the intraday records from

which depth and price impact are computed, and the market center layer supplies the daily characteristics used as controls and as grouping variables. Observations are defined at the stock-day level, and days on which trading is halted, on which the stock is subject to a regulatory news pause, or on which the snapshot record is incomplete are excluded. Because the sample is restricted to large, heavily traded stocks, the estimates describe the relationship for the segment of the market in which institutional execution actually occurs, and they should not be extrapolated to illiquid securities without further evidence.

(2) Variable Settings and Model Construction

Price impact is the explained variable and is measured by the price change caused per unit of active trading volume. Limit order book depth is the core explanatory variable and is measured by the cumulative number or amount of orders at the top five bid and ask levels. Control variables including stock return volatility, trading volume, the bid-ask spread, and market capitalization are introduced to reduce interference from other market factors [7]. The model adopts a panel regression with fixed effects for stocks and for time, and it examines the effect of changes in order book depth on price impact. The baseline specification is

$$PI_{i,t} = \alpha + \beta\, Depth_{i,t} + \gamma' X_{i,t} + \mu_i + \lambda_t + \varepsilon_{i,t} \quad (1)$$

where $PI_{i,t}$ denotes the price impact of stock i on day t, measured as the absolute return per unit of active trading volume; $Depth_{i,t}$ denotes the limit order book depth of stock i on day t, measured as the cumulative amount of orders resting at the top five bid and ask levels; $X_{i,t}$ is a vector of control variables comprising return volatility, trading volume, the bid-ask spread, and market capitalization, with coefficient vector γ; μ_i denotes the stock fixed effect, which absorbs time-invariant characteristics such as industry affiliation, listing venue, and share structure; λ_t denotes the time fixed effect, which absorbs shocks common to all stocks on a given day, including macroeconomic announcements and market-wide liquidity fluctuations; and $\varepsilon_{i,t}$ is the idiosyncratic error term, clustered at the stock level to allow for serial correlation in both depth and impact.

The parameter of interest is β. A negative and statistically significant estimate indicates that a deeper book attenuates the price response to a given trade, which is the mechanism through which liquidity supply reduces execution cost; an estimate that is statistically indistinguishable from zero indicates that price impact is governed mainly by trading activity, volatility, and information asymmetry rather than by posted liquidity, in which case depth is better interpreted as a symptom of liquidity than as a determinant of it. Because depth and impact are jointly determined within the trading day, β is identified from within-stock variation in depth after common daily shocks have been removed, and the lagged depth reported in the robustness tests provides a further check on reverse causality.

Table 1. Variable definitions and measurement. All variables are observed at the stock-day level; price impact and depth are constructed from intraday venue records, and the control variables are constructed from daily market data.

Variable	Symbol	Measurement	Role
Price impact	$PI_{i,t}$	Absolute return per unit of active trading volume, in basis points per million dollars traded	Explained variable
Order book depth	$Depth_{i,t}$	Cumulative amount of orders at the top five bid and ask levels	Core explanatory variable
Return volatility	$Vol_{i,t}$	Realized volatility of intraday returns	Control

Variable	Symbol	Measurement	Role
		over the trading session	
Trading volume	$Volu_{i,t}$	Daily dollar volume	Control
Bid-ask spread	$Spr_{i,t}$	Relative spread, (ask − bid) / midpoint, at the close	Control
Market capitalization	$Size_{i,t}$	Natural logarithm of end-of-day market capitalization	Control
Stock fixed effect	μ_i	Stock-specific intercept	Fixed effect
Time fixed effect	λ_t	Common daily intercept across stocks	Fixed effect
Error term	$\varepsilon_{i,t}$	Idiosyncratic disturbance, clustered by stock	Residual

Note. The subscript i indexes stocks and t indexes trading days. Depth is measured in amount rather than in count in the baseline specification, because an amount-based measure is less sensitive to order fragmentation generated by execution algorithms; the cumulative count at the top ten levels is used as an alternative measure in the robustness tests.

(3) Baseline Regression and Result Analysis

A panel fixed effects model is used for the baseline regression, mainly to examine the direction and significance of the effect of order book depth on price impact. The regression coefficient of the core explanatory variable is the object of interest. If the coefficient of depth is significantly negative, an increase in the number of resting limit orders enhances the market's capacity to absorb trading demand and reduces the influence of large orders on the transaction price; if the coefficient is not significant, price impact is likely to be jointly determined by trading activity, market volatility, and information asymmetry rather than by depth alone. The estimated coefficients of the control variables are used to assess the relative importance of these alternative channels: a positive coefficient on volatility and on the spread is expected if impact compensates liquidity providers for inventory and adverse-selection risk, and a positive coefficient on volume is expected if impact is driven by the intensity of order flow.

Three hypotheses are examined in this framework. The first states that greater depth is associated with smaller price impact, that is, $\beta < 0$. The second states that the magnitude of the effect declines with market capitalization, because large-cap stocks already possess sufficient depth and the marginal contribution of an additional unit of depth is small. The third states that the effect is stronger in high-volatility periods, when liquidity supply is scarce and the book is thin, than in low-volatility periods.

(4) Heterogeneity Analysis and Impact Testing

Given the differences in trading activity and liquidity conditions among stocks, heterogeneity tests are conducted along three dimensions: market capitalization, industry category, and market volatility. The sample is divided into large-cap and mid- and small-cap groups to compare the effect of depth on impact across the two; differences among sectors such as technology, finance, and consumer products are examined by industry category; and trading environments are classified by volatility level in order to analyze the buffering effect of depth under high- and low-volatility states [8]. Group regressions and interaction-term tests are used to identify the situations in which depth affects impact.

The interaction specification takes the form of equation (1) augmented with a term that interacts depth with a group indicator, so that the coefficient on the interaction captures the difference in slope between groups. This is preferable to comparing separate subsample estimates, because the interaction model imposes a common error variance and yields a direct test of the difference rather

than an informal comparison of significance levels across subsets.

(5) Robustness Tests and Result Discussion

To examine the reliability of the baseline results, robustness tests are conducted by replacing the measurement of the core variables, adjusting the price levels at which depth is measured, changing the interval over which impact is computed, and shortening the sample window. For example, the cumulative amount of orders at the top five levels can be replaced by the cumulative number of orders at the top ten levels, in order to check whether the results remain consistent under a different depth indicator; and impact can be computed over different intervals, in order to test the sensitivity of the conclusions to the measurement window. In addition, introducing lagged values of the core explanatory variable can alleviate potential reverse causality. If these tests yield results consistent with the baseline regressions, the conclusions of the study possess good robustness.

Two further checks are worth noting because they bear directly on the interpretation. First, winsorizing price impact at the first and ninety-ninth percentiles guards against the influence of a small number of extreme executions that are unrelated to the depth mechanism. Second, estimating the model on the subsample of days without scheduled macro announcements isolates the variation in depth that is not driven by information events, and a coefficient that survives this restriction is unlikely to reflect announcement effects operating through both variables.

5. Market Optimization and Trading Strategy Implications for Reducing Price Impact

(1) Enhancing Order Book Depth to Improve Market Liquidity

Improving market liquidity requires increasing the effective supply of limit orders and enhancing the stability of the order book. The U.S. stock market can optimize its market-maker incentive mechanisms to encourage liquidity providers to supply limit orders continuously at multiple price levels on both the buy and sell sides, which reduces the deviations of transaction prices caused by insufficient depth. At the same time, trading venues can improve their liquidity evaluation systems by incorporating the number of limit orders, the continuity of quotations, and the frequency of order cancellation into the criteria, so that participants are encouraged to provide stable liquidity support rather than transient quotes. For stocks with low trading activity, optimizing the quotation mechanism can address the imbalance in the distribution of buy and sell orders and enhance the market's capacity to absorb large trades.

The design of such incentives should take account of the finding that depth is environment-dependent. Because the marginal value of depth is highest when liquidity is scarce, an incentive scheme that rewards depth uniformly across states subsidizes liquidity that would have been supplied anyway during calm periods and under-rewards it during stress. Conditioning rewards on the state of the market, for example by scaling them with realized volatility or with the width of the spread, would target the periods in which depth actually reduces impact.

(2) Optimizing Order Allocation to Reduce Trading Impact Costs

Order allocation should determine the number of orders, the number of quote levels used, and the timing of execution on the basis of market liquidity conditions, trade size, and expected price changes. For large trading demands, submitting all orders at once should be avoided; splitting the total volume into several smaller orders and entering the market in phases reduces the consumption of depth caused by concentrated execution [9]. Order size and quote positions should be adjusted dynamically according to the number of limit orders and the changes in price levels on both sides of the book, and execution should be prioritized during comparatively liquid periods. Institutional investors can further balance expected transaction prices, completion requirements, and trading costs, so that order allocation is aligned with the actual absorption capacity of the market.

The trade-off is explicit once the coefficient of interest is known. If a unit increase in depth

reduces impact by β, then the cost saving from waiting for the book to replenish is approximately the product of β, the expected replenishment, and the size of the remaining position, whereas the cost of waiting includes the risk of an adverse price move over the delay. Allocating orders therefore becomes a comparison of these two quantities rather than a matter of convention, and the comparison can be updated as the book changes during the execution.

(3) Improving Dynamic Monitoring to Enhance Risk Response Capability

Market participants should establish a dynamic monitoring system that includes indicators such as order book depth, the bid-ask spread, trading volume, and price volatility, so that changes in liquidity and potential trading risks can be identified promptly. Trading systems can track the number of resting limit orders at multiple levels on both sides of the book; when depth declines rapidly, when the frequency of order cancellation rises abnormally, or when the spread widens markedly, early-warning signals can be issued in time [10]. For specific scenarios such as major economic data releases, corporate earnings announcements, and severe market fluctuations, differentiated risk thresholds can be set, single order sizes reduced, and the trading rhythm adjusted. Historical trading data can be used for stress testing, so that potential price impact under different liquidity conditions can be evaluated and used as a basis for trading decisions.

(4) Improving Execution Strategies to Enhance Trading Efficiency

Execution strategies should be adjusted dynamically according to order size, market depth, and price volatility, so as to avoid the unnecessary trading costs produced by fixed execution methods. For stocks with good liquidity, a Time-Weighted Average Price (TWAP) strategy can be adopted to spread the trade over a preset interval; for stocks with large changes in volume, a Volume-Weighted Average Price (VWAP) strategy can be used to align the execution rhythm with the distribution of market volume. In addition, real-time order book information can be combined with algorithmic trading to adjust quotations, order-splitting ratios, and execution speed dynamically, so that price impact is controlled while completion rates are preserved [11]. By continuously assessing the deviation between actual transaction prices and benchmark prices, algorithm parameters can be further improved and execution quality enhanced.

The common thread across these measures is that depth is not a fixed attribute of a stock but a state variable that responds to incentives, information, and the behavior of other participants. Treating it as such, rather than as a static characteristic to be screened on, is what allows the measures above to be targeted at the moments when they matter.

6. Conclusion

The relationship between limit order book depth and price impact is not a simple linear connection; it is influenced by numerous factors, including stock characteristics, trading periods, market volatility, and investor behavior. The multi-tiered and cross-platform trading structure of the U.S. stock market implies that liquidity supply is heterogeneous, which makes it difficult for static order book indicators alone to reflect actual trading risk. Market participants should therefore strengthen their comprehensive judgment of changes in the order book and in liquidity conditions, and arrange order sizes and execution rhythms accordingly.

The empirical design developed in this paper provides a way to discipline that judgment. By expressing price impact as a function of depth, controls, and two-way fixed effects, the specification separates the contribution of posted liquidity from the contributions of volatility, trading activity, and market-wide conditions, and the heterogeneity tests identify the segments and states in which depth matters most. The resulting estimates are interpretable as the marginal value of depth for execution cost, and they can be used directly in the allocation and monitoring decisions described in Section 4.

Future research can incorporate higher-frequency order data, including order-level messages rather than snapshot records, in order to identify the decay profile of impact and thereby separate its temporary from its permanent component. Extending the sample to smaller-capitalization stocks and to periods of market stress would test whether the relationship estimated here holds outside the liquid segment of the market, and would clarify the conditions under which depth can be treated as a policy target rather than as an outcome.

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