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Empirical Market Microstructure Models: A Review of Trading Behavior, Liquidity, and Price Formation

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Abstract:

This paper reviews empirical market microstructure models and their role in explaining trading behavior, liquidity, price formation, and transaction costs in financial markets. Market microstructure research examines how financial securities are traded and how trading mechanisms, order flow, and information asymmetry influence market outcomes. Unlike traditional financial theories that assume perfect and frictionless markets, market microstructure focuses on the actual trading process, including how prices are determined, how liquidity is provided, and how information is reflected in market prices. The study mainly relied on a literature review approach using secondary sources from academic journals, books, reports, and reputable databases. The review examined classical empirical market microstructure frameworks, focusing on adverse selection models, inventory models, and hybrid models. Classical theories such as the Kyle model, Glosten–Milgrom model, Stoll model, and Ho–Stoll model were reviewed together with more recent hybrid and algorithmic trading frameworks such as the Madhavan–Richardson–Roomans model and the Avellaneda–Stoikov model. The findings show that empirical market microstructure models have evolved from traditional dealer-based frameworks to more advanced models using high-frequency trading data, electronic order books, and algorithmic trading systems. The review further shows that liquidity, bid-ask spreads, and price discovery are influenced by information asymmetry, inventory risk, order processing costs, and trading technology. The study concludes that hybrid empirical models provide a broader explanation of modern market behavior because they combine information effects and inventory management within a single framework. However, many traditional models remain limited by assumptions of rational behavior and perfect information processing. The study recommends further empirical research focusing on emerging markets and the integration of behavioral finance and machine learning approaches into market microstructure analysis.

Keywords: Empirical Market Microstructure, Liquidity, Bid-Ask Spread, Price Impact, Inventory Costs, Information Asymmetry, Inventory Models, Adverse Selection, Hybrid Model

1. Introduction

Market microstructure refers to the processes through which securities are traded in financial markets such as the Nairobi Securities Exchange and the New York Stock Exchange. It focuses on how buyers and sellers interact, the role of brokers and dealers, the different types of trading orders, and the influence of market information on trading decisions (Harris, 2003; O'Hara, 1995). While theoretical models provide a framework for understanding how markets are expected to operate, empirical models rely on actual market data to test and explain these theories. These empirical models help researchers measure important market factors such as liquidity, price volatility, bid-ask spreads, and transaction costs.

Financial markets contribute significantly to economic development by supporting investment, efficient capital allocation, and liquidity creation. However, trading activities in financial markets are influenced by factors such as information asymmetry, liquidity risk, inventory management, and transaction costs (Ighoyivwi & Ehiedu, 2025). To address these challenges, empirical market microstructure models were developed to explain how such factors influence price formation, bid-ask spreads, market liquidity, and trading behaviour (Harris, 2003; O'Hara, 1995). These models have become important in understanding how financial markets function and how trading mechanisms affect market efficiency.

Although numerous studies have been conducted on market microstructure, most empirical evidence is largely based on developed financial markets such as the New York Stock Exchange and NASDAQ, while limited studies focus on emerging and frontier markets (OECD, 2024). This creates a significant gap in understanding how market microstructure dynamics operate in environments where trading activity is lower, liquidity is thinner, and market concentration is higher. In many developing markets, trading is often concentrated among a few large firms, while information dissemination and regulatory systems remain relatively weak compared to developed economies.

Traditional models such as adverse selection models and inventory-based models provide important insights into trading behaviour and market operations. However, these models face limitations in explaining modern market conditions characterized by electronic trading, algorithmic trading strategies, and market fragmentation (University of Bologna, 2024). Furthermore, many traditional models rely on simplified assumptions that may not accurately reflect actual market behaviour, particularly in developing markets where trading activity is lower, transaction costs are higher, regulatory oversight is weaker, and information asymmetries are more pronounced (Ighoyivwi & Ehiedu, 2025). As financial markets continue to evolve through technological innovation and digital trading systems, the relevance and applicability of traditional empirical market microstructure models remain an important area of academic inquiry.

Therefore, there is a need to review and evaluate current empirical market microstructure models in order to understand their relevance, strengths, and limitations in explaining modern financial market behaviour. Such a review will also help identify gaps in existing literature and provide a framework for future studies, particularly in emerging and frontier markets such as Kenya, where improving market efficiency and liquidity remains critical for economic growth. The general objective of this study is to review empirical market microstructure models and examine their role in explaining trading behaviour, liquidity, and price formation in financial markets. Specifically, the study seeks to examine adverse selection empirical market microstructure models, analyze inventory-based market microstructure models, evaluate hybrid empirical market microstructure models, and provide conclusions, recommendations, and limitations arising from the review.

2. Literature Review

2.1 Theoretical Framework

Efficient Market Hypothesis (EMH)

The Efficient Market Hypothesis developed by Eugene Fama argues that security prices fully reflect all available information. According to EMH, abnormal profits cannot consistently be achieved because markets quickly incorporate information into prices (Fama, 1970; Fama, 2021). However, empirical market microstructure research challenges this assumption by showing that transaction costs, asymmetric information, and trading mechanisms influence price formation.

Information Asymmetry Theory

Information asymmetry theory explains situations where some traders possess superior information compared to others. These are known as informed traders and they may exploit private information to earn abnormal profits, creating adverse selection problems for liquidity providers and contributing to wider bid–ask spreads. This creates adverse selection problems for liquidity providers and contributes to wider bid-ask spreads. Models developed by Kyle (1985) and Glosten and Milgrom (1985) are grounded in this theory and remain central to empirical microstructure analysis.

Inventory Theory

Inventory theory focuses on how market makers manage inventory risk. Dealers adjust bid and ask prices to maintain optimal inventory levels and reduce exposure to adverse price movements. This theory explains why bid-ask spreads may widen during periods of market uncertainty or low liquidity (Stoll, 1978).

Behavioral Finance Theory

Behavioral finance recognizes that investors do not always behave rationally. Psychological biases such as overconfidence, herding behavior, and loss aversion may influence trading decisions. Modern empirical market microstructure studies increasingly integrate behavioral finance concepts to explain trading anomalies and volatility patterns (Barberis, 2018).

Market Liquidity Theory

Liquidity theory examines the ability to trade assets quickly without significantly affecting prices. Highly liquid markets exhibit narrower bid-ask spreads, lower transaction costs, and greater market efficiency. Liquidity remains a central concept in empirical market microstructure analysis, especially in emerging markets where liquidity constraints are more pronounced (OECD, 2024).

2.2 Review of Empirical Models

Empirical market microstructure models are significant because they rely on actual trading data to explain how financial markets operate. These models help researchers, investors, and regulators understand market efficiency, trading costs, liquidity, and the role of informed traders in price formation (Hasbrouck, 2007). They also help researchers and regulators assess how trading activities influence price changes and overall market quality, making them essential for both theoretical development and policy application.

Empirical market microstructure models are generally based on three main approaches: information-based also known as adverse selection models, inventory models, and hybrid models. These approaches provide the foundation for empirical analysis and help researchers interpret observed trading behaviour in financial markets (Madhavan, 2000).

Adverse Selection Models

The adverse selection models form an important part of market microstructure theory because they explain how information asymmetry affects financial markets. These models assume that some traders possess more information (informed traders) compared to others (uninformed traders). As a result, market makers and dealers adjust prices and bid-ask spreads to protect themselves from potential losses when trading against informed investors (Kyle, 1985; Glosten & Milgrom, 1985).

Two classical models that remain central in this area are the models developed by Albert Kyle (1985) and Glosten and Milgrom model of 1985. The Kyle (1985) model introduced the distinction between informed and uninformed traders and demonstrated how private information is gradually incorporated into market prices through trading activity. The model showed that informed traders strategically spread their trades over time to maximize profits while minimizing the risk of revealing their information too quickly. Similarly, the Glosten and Milgrom (1985) model explained the bid–ask spread as compensation for the risk faced by market makers when trading with informed investors. These foundational models remain influential in studies of liquidity, trading costs, and price discovery in modern financial markets (Madhavan, 2000; O'Hara, 1995).

Despite their importance, adverse selection models face several empirical challenges. A key difficulty lies in the identification of informed traders, particularly in modern markets characterized by market fragmentation, algorithmic trading, and dark pools. To address this, Easley et al. (1996) developed the Probability of Informed Trading (PIN) model, which estimates the likelihood of informed trading based on order flows. Empirical applications of the PIN model on the NYSE found that informed trading accounted for about 14% of activity in highly liquid stocks, while less liquid securities recorded values approaching 30%, suggesting that liquid markets experience lower levels of information asymmetry.

The PIN model, while innovative, has some limitations. One concern is trade classification errors when determining whether a trade is buyer- or seller-initiated. Ellis et al. (2000) showed that classification methods may misidentify trades in 20–25% of cases, potentially biasing PIN estimates downward (Grammig & Theissen, 2002). Another critique relates to the assumption of constant order arrival rates, which may not reflect actual market conditions during periods of volatility or major information releases (Easley et al., 2001; Lei & Wu, 2005)

Extensions of the PIN model attempted to address these weaknesses. For instance, Venter & De Jongh (2002) modified the framework to allow uninformed liquidity traders to respond to information events without altering the overall findings. More recently, scholars have sought to refine adverse selection models to better capture the effects of high-frequency trading, fragmented markets, and hidden liquidity environments (Boulatov & George, 2022). These refinements highlight the ongoing relevance of adverse selection theory but also underscore the need for contextual adaptation in emerging markets, where liquidity is thinner and information asymmetry may be more pronounced.

Inventory Models

Inventory-based models are an important component of market microstructure theory because they explain how market makers and dealers manage trading risk through quote adjustments. Unlike adverse selection models, which emphasize information asymmetry, inventory models focus on how dealers adjust bid–ask spreads to reduce risks associated with holding securities (Stoll, 1978; Ho & Stoll, 1981).

The Stoll (1978, 1989) model argued that market makers continuously adjust bid and ask quotes to manage inventory risk. Dealers' lower prices when they hold excess inventory to encourage buying, and raise prices when inventory is low to attract sellers. This links spread determination directly to dealer inventory positions and liquidity conditions.

The Ho–Stoll (1981) model extended this framework by introducing an optimal quote-setting mechanism. Prices were modeled as fluctuating around the asset's fundamental value depending on inventory levels: $P=P^* -\lambda I$

Where P is the quoted price, $P*$ is the fundamental value, I is inventory level, and λ measures sensitivity to inventory risk. This model demonstrated that bid–ask spreads compensate dealers for inventory risk, order processing costs, and adverse selection exposure. Empirical evidence shows that spreads widen during periods of high uncertainty and narrow when liquidity improves (Menkveld, 2013).

The strength of the inventory models is that they provide a practical framework for understanding transaction costs and liquidity provision. They highlight how spreads reflect not only information asymmetry but also the costs of holding risky positions. This is particularly relevant in emerging markets, where trading is less frequent and liquidity constraints are more pronounced (Madhavan, 2000).

Despite its contributions, the Stoll and Ho–Stoll models have several limitations. Firstly, the models assume rational behaviour and optimal decision-making among market participants, while actual markets are often influenced by behavioural biases such as herding, overreaction, and speculative trading. Second, the models largely ignore competition among market makers and institutional dominance, conditions that are particularly important in emerging markets where a few large blue-chip firms may control significant trading activity. Third, the models do not fully account for modern developments such as algorithmic trading, high-frequency trading, and machine-learning-based decision systems, which now play a major role in liquidity provision and price formation (Cartea, et al., 2015).

These limitations have contributed to the development of newer hybrid models such as the Avellaneda- Stoikov model of 2008. The Avellaneda–Stoikov framework integrates inventory management with algorithmic trading strategies and focuses on optimal spread determination in electronic markets. The model is particularly relevant in modern markets where automated trading systems continuously adjust quotes in response to market volatility, inventory exposure, and order flow information (Avellaneda & Stoikov, 2008).

Inventory models remain highly relevant in emerging stock markets such as the Nairobi Securities Exchange (NSE). Actively traded securities like Safaricom Public Limited Company (PLC), Equity Group Holdings PLC, and Kenya Commercial Bank

(KCB) Group PLC exhibit narrow spreads due to high liquidity and strong market participation. Smaller-cap firms, however, often experience wider spreads because of lower trading frequency and reduced liquidity. This demonstrates the importance of market concentration and trading activity in determining liquidity patterns within emerging financial markets.

Hybrid Framework

Hybrid market microstructure models integrate the key elements of information-based models and inventory-based models to provide a more comprehensive explanation of trading behaviour, liquidity provision, and price formation. While information-based models emphasize the role of asymmetric information between informed and uninformed traders, and inventory models focus on dealer risk management, hybrid frameworks combine both perspectives to explain trading behaviour, bid-ask spread determination, and market liquidity simultaneously (Madhavan et al., 1997).

The development of hybrid models emerged from the realization that neither adverse selection models nor inventory models alone could fully explain observed market behaviour. In actual financial markets, dealers face both inventory risk and the possibility of trading with informed investors. As a result, hybrid models attempt to capture the combined effects of information asymmetry, inventory management, and order processing costs within a single empirical framework. These models are therefore considered more realistic representations of modern financial markets (O'Hara, 1995).

The Madhavan–Richardson–Roomans (MRR) model is one of the most influential hybrid frameworks. It demonstrates how trade direction, order flow, and inventory effects jointly influence price changes. The model highlights that market prices respond not only to private information embedded in trades but also to the inventory positions of dealers, thereby linking information effects directly to liquidity and transaction costs (Hasbrouck, 2007). This integration makes hybrid models more realistic representations of actual market conditions compared to single-theory approaches.

Hybrid models are particularly relevant in modern electronic and fragmented markets, where trading occurs across multiple platforms and both information asymmetry and inventory management shape spreads and liquidity. The rise of algorithmic and high-frequency trading has further strengthened the importance of hybrid frameworks. For example, the Avellaneda–Stoikov (2008) model extends traditional microstructure theory by incorporating stochastic control methods for optimal quote setting. It shows how market makers dynamically adjust bid–ask spreads in response to volatility, inventory exposure, and order flow intensity, making it highly applicable in contemporary electronic markets (Cartea et al., 2015).

In emerging markets such as the Nairobi Securities Exchange (NSE), hybrid models also provide valuable insights. Large-cap firms like Safaricom PLC and Equity Group Holdings PLC exhibit trading patterns shaped by both informed trading and liquidity management, while smaller firms often face wider spreads due to lower liquidity and higher uncertainty. This demonstrates the practical relevance of hybrid models in explaining market behaviour across different contexts.

Nevertheless, hybrid models are not without limitations. Many rely on simplifying assumptions such as rational behaviour, stable order arrival rates, and efficient information processing. These assumptions may not fully reflect actual market conditions characterized by behavioural biases, sudden volatility, and strategic algorithmic trading. Moreover, empirical estimation often requires high-frequency trading data, which may be difficult to obtain in developing markets. Despite these challenges, hybrid models remain important because they provide a more holistic framework for understanding price discovery, liquidity provision, and trading costs in both developed and emerging financial markets.

3. Research Methodology

This study adopted a literature review approach because of time limitations and the exploratory nature of the research. The study mainly relied on secondary sources of data, including peer-reviewed journal articles, books and conference proceedings. The purpose was to examine how these models explain liquidity, price formation, bid-ask spreads, and trading behaviour in financial markets, while also identifying their relevance and limitations in order to provide a theoretical and conceptual foundation for future empirical studies, especially in the context of emerging markets.

The search process was conducted across several academic databases and repositories, including Google Scholar, ScienceDirect, Emerald Insight, and university digital libraries. A combination of broad and specific keywords was employed to capture relevant studies. Key search terms included "empirical market microstructure models," "market microstructure," "inventory models," "hybrid models," "information asymmetry," "bid–ask spread," "adverse selection," "liquidity," "price discovery," "algorithmic trading," "emerging markets," and "Nairobi Securities Exchange." These terms were refined to ensure comprehensive coverage of the literature.

The inclusion criteria focused on peer-reviewed journal articles, books and reports from credible institutions. Sources were selected based on their relevance to the research objectives, methodological rigor, credibility of authors, and contribution to market microstructure literature. Preference was given to studies published within the last ten years to capture current developments in electronic trading, algorithmic strategies, and market fragmentation. However, a few classical studies such as Kyle (1985), Glosten and Milgrom (1985), Stoll (1978) and Ho-Stoll (1989) were retained due to their foundational contributions to market microstructure theory.

The collected literature was reviewed and analysed thematically. The analysis focused on the theoretical assumptions, empirical findings, strengths, weaknesses, and practical relevance of the different empirical market microstructure models. Comparisons were also made between findings from developed financial markets and emerging markets such as the NSE in order to identify existing research gaps and areas requiring further empirical investigation.

4. Findings and Discussion of Findings

The reviewed literature shows that empirical market microstructure models are important in explaining how prices, liquidity, and trading behaviour interact within financial markets. Evidence suggests that no single theoretical approach can fully capture market dynamics; instead, information-based models, inventory-based models, and hybrid models each contribute distinct insights into the trading process (Hasbrouck, 2007; Madhavan, 2000).

The findings from adverse selection models show that information asymmetry remains a major factor influencing market efficiency and price formation. Early studies by Kyle (1985) and Glosten and Milgrom (1985) showed that informed traders influence prices by exploiting private information while bid–ask spreads partly compensate dealers for the risk of trading with such investors.

Empirical applications of the Probability of Informed Trading (PIN) model revealed that illiquid stocks tend to experience higher levels of informed trading compared to highly liquid securities suggesting that liquidity reduces the effects of information asymmetry (Easley et al., 1996). However, these models face limitations, particularly in fragmented markets with algorithmic trading and dark pools. The difficulty of accurately identifying informed traders and the reliance on assumptions such as constant order arrival rates and correct trade classification weaken their empirical reliability (Ellis et al., 2000; Grammig & Theissen, 2002).

The literature on inventory models emphasizes the importance of dealer risk management in determining liquidity and bid-ask spreads. Frameworks developed by Stoll (1978, 1989) and Ho & Stoll (1981) show that market makers adjust quotes to balance inventory positions, lowering prices when holding excess securities and raising them when inventory is scarce. Empirical evidence consistently indicates that liquid markets exhibit narrower spreads and lower transaction costs, while illiquid markets face wider spreads due to higher uncertainty (Menkveld, 2013).

Evidence from emerging markets such as the Nairobi Securities Exchange (NSE) supports these findings, with actively traded firms like Safaricom PLC and KCB Group PLC showing tighter spreads compared to smaller-cap firms with lower liquidity. Nonetheless, inventory models are criticized for assuming rational behaviour and ignoring behavioural biases such as speculation and herd behaviour. They also inadequately account for competition among market makers and modern developments such as algorithmic and high-frequency trading (Cartea et al., 2015).

The reviewed literature suggests that hybrid models provide a broader explanation of market behaviour because they combine information asymmetry and inventory risk within a single framework. Studies based on the Madhavan–Richardson–Roomans (MRR) model found that both private information and dealer inventory pressures influence price movements, offering a more complete explanation of spread determination and liquidity dynamics (Madhavan et al. , 1997). Hybrid models are particularly relevant in electronic and fragmented markets, where both information effects and inventory management shape trading outcomes. The Avellaneda–Stoikov (2008) model further extends this approach by incorporating algorithmic decision-making and stochastic control, showing how spreads adjust dynamically in response to volatility, inventory exposure, and order flow. While hybrid models provide more realistic insights, they also face challenges, including reliance on high-frequency trading data that may not be available in developing markets and assumptions of rational behaviour that overlook behavioural biases (Boulatov & George, 2022).

Overall, the findings indicate that empirical market microstructure models have evolved to capture different aspects of trading behaviour. Information-based models explain the role of private information, inventory models highlight dealer risk management, and hybrid models combine both perspectives to better reflect modern electronic markets. However, much of the empirical evidence is drawn from developed markets such as the NYSE and NASDAQ, leaving a significant gap in understanding liquidity behaviour, informed trading, and spread dynamics in emerging financial markets such as Kenya. Addressing this gap is crucial for developing models that reflect the realities of frontier markets, where liquidity constraints, market concentration, and behavioural factors play a more pronounced role.

5. Conclusion and Recommendations

5.1 Conclusion

The review of empirical market microstructure models demonstrates their importance in explaining the interaction between prices, liquidity, and trading behaviour in financial markets. Information-based models explain the role of private information and informed trading in shaping bid–ask spreads and price formation (Kyle, 1985; Glosten & Milgrom, 1985). Inventory models emphasize how market makers manage inventory risk and liquidity provision through quote adjustments (Stoll, 1978; Ho & Stoll, 1981). Hybrid models, such as the Madhavan et al., (1997) and Avellaneda–Stoikov (2008) frameworks, integrate both perspectives to provide a more comprehensive explanation of spread determination and market quality in modern electronic markets.

The literature further shows that bid-ask spreads are influenced by information asymmetry, inventory risk, and order processing costs, with highly liquid securities generally experiencing narrower spreads and lower transaction costs compared to illiquid securities (Hasbrouck, 2007; Menkveld, 2013). However, traditional empirical market microstructure models face limitations in addressing modern developments such as algorithmic trading, high-frequency trading, and fragmented markets. Moreover, most empirical evidence is drawn from developed markets, leaving a significant gap in understanding liquidity behaviour and informed trading in emerging markets such as Kenya's NSE.

5.2 Recommendations

Future research should prioritize emerging and frontier markets, particularly African exchanges, to address the lack of region-specific evidence on liquidity, spreads, and informed trading. Researchers should also integrate behavioural finance concepts into empirical models, recognizing that investor sentiment, panic trading, and herd behaviour influence market outcomes.

There is a need to develop updated empirical frameworks that reflect modern electronic trading environments. Hybrid models incorporating information asymmetry, inventory risk, and technological factors such as algorithmic and machine-learning-based trading may provide more realistic explanations of contemporary market behaviour.

For policymakers and regulators, strengthening transparency and surveillance systems is critical to reducing information asymmetry and enhancing investor confidence. Improved disclosure requirements, efficient reporting mechanisms, and stronger oversight can contribute to greater liquidity and efficiency in developing markets.

Finally, future empirical research should make use of high-frequency and transaction-level data where available. Such data can provide deeper insights into trading behaviour, liquidity patterns, and the effects of market structure changes on price discovery.

5.3 Limitations of Findings

This study was based on a review of existing literature and relied primarily on secondary sources such as journal articles, books, and reports. No primary data collection or empirical testing was conducted, limiting the ability to verify the applicability of the models within specific markets such as the NSE as such the findings cannot be generalized.

In addition, financial markets continue to evolve rapidly due to technological developments such as algorithmic trading, artificial intelligence, and high-frequency trading systems. Some classical market microstructure models reviewed in this study were developed before these technological changes became widespread. Therefore, certain assumptions and conclusions from earlier models may not fully reflect current market realities.

Finally, the study focused mainly on information-based, inventory-based, and hybrid empirical market microstructure models. Other related areas such as behavioral finance and regulatory market structure reforms were not examined in detail. This may limit the breadth of the discussion on emerging trends within financial markets.

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