A MONTE CARLO ANALYSIS OF THE DETERMINANTS OF MARKET LIQUIDITY AND ITS IMPLICATIONS FOR REGULATORY POLICYMAKERS

Ádám Czelleng *

* Budapest Business University, Budapest, Hungary
Contact details: Budapest Business University, Building E, 2nd Floor, Room 39, Diósy Lajos Street 22-24, 1165 Budapest, Hungary

OPEN ACCESS

How to cite this paper: Czelleng, Á. (2024). A Monte Carlo analysis of the determinants of market liquidity and its implications for regulatory policymakers. *Journal of Governance & Regulation, 13*(3), 224–237. https://doi.org/10.22495/jgrv13i3art19

ISSN Print: 2220-9352
ISSN Online: 2306-6784

Received: 04.11.2023
Accepted: 12.08.2024

JEL Classification: D02, D53, E43, G12, G20, G24
DOI: 10.22495/jgrv13i3art19

Abstract

The paper aims to understand the determinants of bid-ask spread and how the liquidity within a dealer-driven financial market is affected by different rules and behaviours. As the output of the three-agent Monte Carlo simulation within this paper shows, the liquidity of financial markets can be considered to be a rather complex phenomenon. The paper also distinguishes low, medium and high levels of information asymmetry. The simulation results confirm that informed traders contribute to wider spreads due to a high level of information asymmetry while at medium and low degrees of information asymmetry, the proportion of informed traders increases the liquidity before decreasing. This result supports the arguments postulated by the theoretical background of some empirical works which surprisingly find that liquidity increases when there is more active informed trading. Four important economic implications have been addressed as a consequence of the results. These are related to the efficiency of the regulation, the limitations of micro-and macroprudential regulation, central bank policy and the commonality in liquidity.

Keywords: Spread Determinants, Monte Carlo Simulation, Market Liquidity, Market Microstructure, Information Asymmetry

Authors' individual contribution: The Author is responsible for all the contributions to the paper according to CRediT (Contributor Roles Taxonomy) standards.

Declaration of conflicting interests: The Author declares that there is no conflict of interest.

Acknowledgements: The Author extends the deepest gratitude to those whose insights, expertise, and support were instrumental in both the research and the preparation of this manuscript. Furthermore, the Author wishes to express sincere appreciation to Budapest Business University for their essential support throughout this endeavour.

1. INTRODUCTION

In recent decades, financial markets have undergone significant changes. Szunke (2014) identifies five factors that contributed to this process. These are globalisation, deregulation, the reduced role of intermediaries, technological change and firms consolidation. As firms have immediate access to financial markets, the proportion of immediate capital market financing is rising. Financial innovation is linked to this topic too, because firms are issuing new securities designed to cover their risks. As a result of the changes and reduced interest rates, central banks invented new tools, while shifting their focus from interest rate policy to balance sheet policy which has had a significant impact on assets and thus on markets as well. Normally, central banks during times of financial crisis assume the role of lender of last resort, thereby providing the market with unlimited funding. However, today central banks assume the role of the dealer of last resort. The crisis pointed out that macroeconomic stabilization cannot be reached by only price stability. Liquid financial markets are desirable for economics for many reasons. Higher liquidity means higher efficiency in source and information allocation. Therefore, central banks can intervene in the market in a more efficient way and central banks can even use indirect monetary policy tools as the transmission channel is stable and the effects of central banks' operations are predictable. Liquidity has a significant role in determining financial institutions' behaviour as liquid markets allow banks to take larger maturity mismatches and also currency mismatches between assets and liabilities. Liquidity also has an impact on crisis management as financial and non-financial companies can fund their operation more easily. As a result of that liquidity has been in the focus of academia recently due to its strong relevance to any financial markets.

Liquidity has various dimensions and definitions but liquidity for an asset market evaluates its potential to be traded quickly at large volume without an impact on the current price on the market.

We can distinguish dealer-driven and order-driven markets. This paper focuses on dealer-driven markets where market makers act as intermediaries between the sellers and buyers of securities. The price that market makers set for the buyers is called the ask or offer price, while the price set for sellers is called the bid price. The market makers or so-called (security) dealers make their profit from the difference between ask and bid price so they are paid for providing market liquidity.

The bid-ask spread is considered to be a good proxy for liquidity on quote-driven and order-driven markets as well as a narrow spread can mean a liquid market while widespread can signal an illiquid market.

There has been dynamic growth of the literature in both theoretical and empirical modelling of the bid-ask spread and its components. The majority identifies three main elements which determine the bid-ask spread. These elements are the inventory carrying cost, adverse selection cost and order processing costs.

It is important to have a better understanding of market liquidity as it could affect asset pricing and vehicles' profit. We also need to understand how liquidity is affected by the asset purchasing programs of the central banks in order to increase liquidity and maintain financial stability with less social costs.

For analysing the determinants of the bid-ask spread and the positioning of prices, a three-agents model with Monte Carlo simulation was considered as the most appropriate method to investigate. This is because it allows us to analyse a wider variety of scenarios and also lets us analyse the impact of different factors. In the model, we can distinguish market makers, uninformed traders and informed traders who are traders with fundamental information about the true value of the security.

The conducted model captures the complexity of the market so parameters which were previously ignored by the literature and their impact on the bid-ask spread are also analysed, i.e., risk sensitivity, risk-taking willingness and so on.

We can distinguish various types of impact on the bid-ask spread. These are the following:

- effects from the dealer market;
- effects from the security's market;
- effects from the trader;
- information asymmetry.

One of the contributions of this paper is to determine how the changes in different factors, behaviours and rules affect the bid-ask spread. Whenever the value of any parameter is changed, ceteris paribus, we can detect its impact on the spread. As all of the parameters are interpreted as a dealer or trader behaviour or indeed a feature of the market, we can detect how these factors can influence the bid-ask spread and thus the market liquidity. Another contribution of this paper is the applied innovative way to analyse the impact of the factors with various assumptions and initial parameters. The impact of the factors is analysed in various scenarios. Due to the complexity of the model, multidimensional results are shown, therefore, multiplier effects and interrelations are able to be captured. Chulia et al (2023) empirically analyzed the liquidity of financial markets and identified that liquidity is a complex, non-linear phenomenon.

Further significant contribution of the paper is the impact of information asymmetry on the spread as the paper distinguishes low, medium and high levels of information asymmetry between market participants. The simulation results confirm that informed traders contribute to wider spreads due to a high level of information asymmetry while at medium and low degrees of information asymmetry, the proportion of informed traders increases the liquidity before decreasing. This result supports the arguments postulated by the theoretical background of some empirical works (Cornell & Sirri, 1992; Coling-Dufresne & Fos, 2015) that empirically analysed the relationship between adverse selection and liquidity. The papers surprisingly find that liquidity increases when there is more active informed trading.

The remainder of this paper is organized as follows. Section 2 provides a review of the existing literature on market liquidity. Section 3 describes the simulation-based model, including the setup of actors' behaviour within the model. Section 4 presents a summary of the model's results under various scenarios. Section 5 discusses the findings. Finally, Section 6 outlines the implications of the results, framing them within their broader economic context.

2. LITERATURE REVIEW

Building on Grossman and Miller (1988), Harris (1991) introduced that the liquidity of markets can be characterised by various interconnected dimensions, such as tightness or width, immediacy, depth, breadth, and resilience. According to Sarr and Lybek (2002), liquidity measures can be classified into four groups: 1) transaction cost measures; 2) volume-based measures; 3) equilibrium price-based measures; and 4) market impact measures. From these four groups, we will focus on one of the key transaction cost measures, the bid-ask spread.

The order-driven market is one in which all orders of buyers and sellers are listed along with the price at which they are willing to buy or sell the security. In order-driven markets volatility, turnover and market concentration are considered to be the determinants of the bid-ask spread (Copeland & Galai, 1983; Wei, 1994; Váradi, 2012). Some paper examines the sources of commonality in liquidity on demand and supply side (Karolyi et al., 2011; Coughenour & Saad, 2004; Hasbrouck & Seppi, 2001; Koch et al., 2016). Market-wide liquidity is identified as a fundamental factor influencing price formation, alongside traditional factors like value, growth, profitability, investment, and market dynamics, suggesting its integral role in asset pricing models (Amihud & Noh, 2020).

The literature identifies three elements which determine the bid-ask spread on quoted markets: the inventory carrying cost, adverse selection cost and order processing costs. Some also consider market structure costs for oligopolistic markets.

Amihud and Mendelson (1980) published their famous paper about market-making with inventory. Their study describes the behaviour and profit-maximizing conditions of price-setting monopolistic market makers. The main purpose of the paper is to describe the inventory-dependent behaviour of the market makers. The study uses various underlying assumptions for their model which are related to the behaviour of the dealer, the distribution of the trading activity, transaction costs and so on. The paper concludes that market makers have a preferred inventory position which is aimed at the dealer's pricing. It confirmed Bagehot's (1971) results that market makers trade with liquidity-motivated traders.

Glosten and Milgrom (1985) introduced the concept of informed and uninformed traders that dealt with the information asymmetry between the market participants. In the Glosten-Milgrom Model, the market maker sets the bid and ask price and a trader is randomly chosen each time an order of units is submitted. If the chosen one is an informed trader, then it is willing to buy if it can purchase the security at a better price than its real value and the opposite for selling. If the randomly chosen trader is an uninformed one, the options are bought or sold in a random manner. Two important consequences are considered as the result of the model. One is the learning process of the market makers as the market maker does not know which type of trader the order is from so the dealer continuously adjusts its belief about the value of the security. Another justification is that asymmetric information induces the spread.

O'Hara and Oldfield (1986) analysed how the bid-ask spread is set in a dealer-driven market. The study points out that the bid-ask spread is affected by a portion of the known limit orders, a risk-neutral adjustment for expected market orders, and a risk adjustment for market order and inventory value uncertainty. It is demonstrated that inventory has a pervasive role in affecting both the placement and size of the spread.

Treynor (1987) introduced the term of value-based investors. They are able to fulfil the dealer function but at a significantly larger bid-asked spread than the market maker. Compared to the value-based investor, the dealer has limited ability and willingness to absorb risk, therefore, the market makers suffer constraints based on the position — long or short — he is willing to take. The value-based investors in fact determine the price which in turn drives the dealer's price. Treynor's revolutionary idea was very simple but useful as it was built for the security market, but it could be adapted to the money market as well. His model describes the behaviour of markets in which the participants face price risk (or liquidity risk).

Wang (2014) used a simulation method to analyse the bid-ask spread. Wang (2014) used an extended Glosten-Milgrom model (Glosten & Milgrom, 1985) under a Bayesian Markov chain Monte Carlo model based on high-frequency trade data. The basic assumptions are equal to the Glosten-Milgrom model's assumptions, i.e., the market maker sets the bid and ask price in every period, while there are two types of traders: uninformed and informed. At a given moment, a single trader is randomly selected and allowed to place either a buy or a sell order for one unit of the security.

There has been a rapidly growing demand for theoretical and empirical models analysing the liquidity of financial markets because of the roots and consequences of the financial crisis in 2008–2009. In order to maintain the stability of the financial system, central banks do not only need to aim for the stability of institutions but also the stability of markets. In dealer-driven markets, liquidity can evaporate if dealers are not able to adjust their inventory or do not want to allow their balance sheet to expand. In these cases, liquidity cannot be restored by lending to financial institutions, but central banks can offer wider bid-ask spread than the market would offer under normal conditions — peacetime — thus the central bank puts a liquidity floor to key markets. Overall, central banks can significantly moderate both the probability and impact of liquidity shocks. In spite of the significant relevance and beneficiaries of this role of central banks, the rise of moral hazard, adverse selection and soft budgetary constraints are considered as significant adverse effects of the dealer of last resort. We need a better understanding of how the prices and spreads are positioned on dealer-driven markets and how the liquidity is affected by the asset purchasing programs of the central banks in order to increase liquidity and maintain financial stability with less social costs (Bélyácz & Szász, 2014; Mehrling, 2014). Schwartz et al. (2020) introduce "latent" liquidity to enhance the understanding of market liquidity beyond traditional measures, like posted orders, examining its impact on equity prices, market structure, and asset pricing. It advocates for regulatory policies to improve market quality and liquidity, highlighting the consensus on the economic advantages of more liquid financial markets.

Chulia et al. (2023) introduce innovative market-wide liquidity indicators by examining the tails of liquidity distribution, diverging from traditional methods that average individual indicators. The research constructs aggregate liquidity measures from low and high quantiles of six liquidity metrics, revealing asymmetric impacts on liquidity distribution tails and testing for nonlinear effects of market determinants on liquidity. In line with this, the rising significance of algorithmic high-frequency traders and the expanding influence of artificial intelligence and machines responsible for executing the majority of market transactions, often linked to more liquid markets and reduced spreads, have paved the way for novel nonlinear dynamics in the relationship between market liquidity and volatility (Baldauf & Mollner, 2020).

3. RESEARCH METHODOLOGY

To analyze the determinants of the bid-ask spread and price positioning, a three-agent model incorporating Monte Carlo simulation, rooted in microstructure theory was applied. This approach distinguishes between market makers, uninformed traders, and informed traders, allowing exploration of a broad array of scenarios to understand market dynamics. It serves as a computational technique for simulating economic processes as dynamic systems of interacting agents, enabling insights into the bid-ask spread and market liquidity through the complex interplay and emergent properties of financial agents.

Although empirical research faces challenges in categorizing actors into these roles, this classification aligns with the goals of prior studies (Cornell & Sirri, 1992; Coling-Dufresne & Fos, 2015). Beyond big data methods, leveraging principal components that proxy information asymmetry and high-frequency models with time lags can help clarify causality. Additionally, constructing microstructure models is crucial for a deeper analysis of market liquidity relationships.

3.1. Market maker

Drawing on the theoretical models of Treynor (1984), Gromb and Vayanos (2002), Brunnermeier and Pedersen (2009), and empirical evidence from Jylha (2016), our paper posits that market liquidity is influenced by dealers' funding liquidity. This foundational assumption underpins our model where market makers, who monopolize trading by setting both ask and bid prices, adjust prices based on their net buying or selling position, influencing their risk exposure on the balance sheet. Market makers' pricing strategy aims to balance risk by adjusting the spread within the constraints of the outside spread, defined by value-based traders.

Treynor (1987) highlights that market makers can't arbitrarily set prices; they operate within an external spread, adjusting prices and spreads based on their risk positions. Our model adopts this principle, asserting that price adjustments are a strategic response to balance sheet risks — prices decrease with increased long risk and rise with higher short risk. This dynamic reflects the fundamental finance principle that higher risk commands higher returns. Our assumptions include risk symmetry between short and long positions and the market maker's awareness of the security's basic value, aiming to adjust their balance sheet in response to their current risk position. To simplify, we apply quadratic functions for bid and ask prices, allowing for a clear representation of the market maker's strategy in adjusting prices and spreads in accordance with their risk profile and the foundational value of securities.

$$a = N[n(x-k)^2 + u - \frac{1}{2}\lambda, historical\ standard\ deviation] \quad (1)$$

$$b = N[-n(x+k)^2 + u + \frac{1}{2}\lambda, historical\ standard\ deviation] \quad (2)$$

where, x is the risk in the market maker's balance sheet; k is the maximum long/short risk the market maker is willing to tolerate in its balance sheet; u is the economic value of the security; n is a risk sensitivity factor. The λ parameter is delivered by Eq. (3) as it is considered to determine the expected return of the market maker on trading a single security (buying and selling) with no risk in the balance sheet. This factor is affected by the market maker risk sensitivity, market maker risk tolerance and the risk-free return. The λ parameter also determines the exposure when the market maker starts aggressively adjusting its balance sheet, i.e., set the offer price lower than the fundamental and set the bid price higher than the fundamental price.

$$\lambda = 2n * k^2 - \frac{risk.free.rate}{\frac{std}{n}} \quad (3)$$

Based on Eq. (1) is a downward sloping function on [$-k$; $+k$] and at $+k$ its value is u. The fundamental value of the security follows a geometric Brownian motion (as it was assumed), so changes in bid and ask prices are considered to have a distribution really close to the geometric Brownian motion.

Since it is a convex function we can accept the assumption, that the valuation of a security can aid the market provider in its goal of adjusting its balance sheet which is as large, long or short risk.

Similar statements can be made about Eq. (2) as it is equally downward sloping on [$-k$; $+k$] and at $-k$ its value is u but the bid price function is a concave function allowing the market provider to modify its balance sheet.

Based on equations (1) and (2) we can denote the mid-price function, which is determined as Eq. (4).

$$mid = \frac{a+b}{2} \quad (4)$$

The mid-price is the same as the economic value solely in case the market provider has net zero risk. This means that the tightest spread is utilized around the mid-price if the mid-price is the same as the economic value.

The spread used is thus also determined by the market maker's balance sheet exposure, due to the fact that the actual short/long position simultaneously determines the ask and the bid prices.

$$spread = a - b \quad (5)$$

Based on the spread equation we can conclude that the utilized spread is independent of the economic value of the security. In case there is no risk of exposure the spread is $2nk^2$, yet the profit acquired depends on the supply and demand curve (in an ideal case p_{mid} is p^* at net zero risk so traded volumes are 1, more or less equal).

3.2. Traders

From the literature, we can distinguish informed and uninformed traders in the model (Wang, 2014; Das, 2005; Glosten & Milgrom, 1985). In the model, α is assumed as the proportion of informed traders and β is a proportion of uninformed traders. α and β add up to 1 and the net position of traders (informed and uninformed) is offset by the net position of the market maker, so traders are only allowed to deal with the market maker. A short position is only ruled out for the traders and not for the market maker. The model does not include taxes and other transaction costs (charges) for any agents.

The informed traders are able to properly evaluate the arising information hence they have knowledge about the value of the underlying asset. Thus, informed traders who are assumed to know V_t, will place a buy order if the fundamental value is higher than the ask price ($V_t > A_t$) or a sell if the fundamental value is lower than the bid price ($V_t < B_t$) or no trade at all otherwise. Whenever the informed trader is satisfied with the trading condition at time t, the trading volume is generated by a normally distributed stochastic process with mean 1 and variance σ^2 but both parameters are also input parameters of the simulation. So, the probability of informed trades is described by Eq. (6) and the trading volume of informed traders is described by Eq. (7).

$$Probability\ of\ informed\ trade_t = \int_{-\infty}^{B_t} [f_t(v)]\, dv + \int_{-\infty}^{A_t} [f_t(v)]\, dv \tag{6}$$

where, B_t is the bid price, A_t is the ask price at t and $f_t(v)$ is the normal density of the fundamental value.

$$Informed\ trade\ quantity_t = \alpha \int_{-\infty}^{\infty} f_t(f)\, df \tag{7}$$

where, α is the proportion of informed traders and $f_t(f)$ is the normal density of the trading process distribution.

The non-informed or ordinary traders do not know the real value of the securities, therefore, their decision does not depend on the changes in the fundamental value. Non-informed traders will place a buy or a sell with an equal probability of γ or keep their position with a probability of $1 - 2\gamma$. In the case of trading, uninformed actors trade (buy or sell) a random number determined by the normal distribution in which the parameters are also parts of the simulation independently from the stochastic process which generates the trade size for informed trades. The probability of uninformed trades is described by Eq. (8) and the trading volume of uninformed traders is described by Eq. (9).

$$Probability\ of\ uninformed\ trade_t = 2\gamma \tag{8}$$

$$Uninformed\ trade\ quantity_t = (1 - \alpha) \int_{-\infty}^{\infty} f_t(f)\, df \tag{9}$$

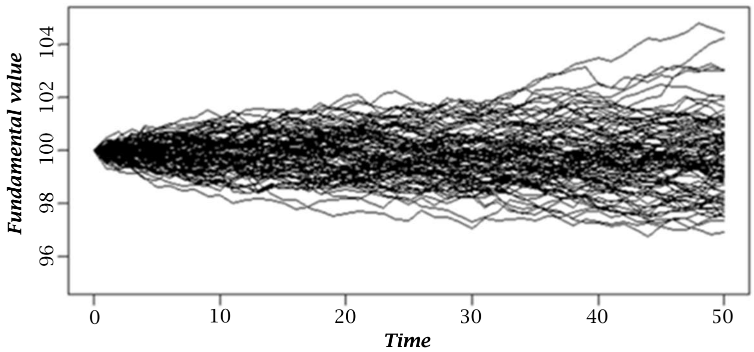
The uninformed traders' probability for buying or selling was adjusted for analysing the overheat or fire sales in the model in order to help us understand the liquidity impact resulting from behavioural changes (animal spirit or herd behaviour). In that case, the probability of buying is μ while the probability of selling is $1 - \mu$, therefore, this scenario does not include the possibility of non-acting. The uninformed traders either buy or sell the security in each of the 50 periods.

The model highlights that market prices can significantly deviate from fundamental values due to the activities of uninformed traders, who may persistently buy or sell. Such scenarios, akin to asset bubbles, are treated as rare within the model, thus, their influence on simulation outcomes is considered moderate. Market corrections are influenced by the market maker's risk tolerance and their willingness to adjust their balance sheet. Characteristics like overconfidence and bounded rationality, typical of behavioural finance, are not incorporated in this dissertation. Future research could explore the effects of behavioural traits on market dynamics, necessitating modifications to the model's assumptions on expectations and budget constraints.

3.3. Model parameters

The simulation program was written in an R software package. 50 periods (sequences) of pricing and trading were modelled and simulated a thousand times. Market makers and traders enter the market sequentially in every period, the market maker sets the price while traders can buy the security at ask price (A_t) and sell the security at the bid price (B_t). Information arises about the security in every period which determines the fundamental value (V_t) of the security at time t but only the market makers and the informed traders know the proper value of the security. The true underlying value of the security (V_t) at time $t = 0, 1, \ldots, 50$ follows a random walk, therefore, $V_t = V_t - 1 + \varepsilon_t$, where the ε_t is following normal distribution, which parameters are integrated as part of the simulation. Simulating the fundamental value a hundred times using the assumptions of random motion generates the following price path with the initial price (price at t_0) 100.

Figure 1. Price simulation a hundred times



Source: Author's elaboration.

The agent computational models need to specify the initial state of the system by specifying agents' initial data and behaviour. In this model, 12 parameters are set to determine the initial state at time 0 then the dynamic interactions between the agents are managed automatically.

Table 1. Benchmark parameters for the initial state

Parameter	*Initial value*
Initial price of security	100
Security's return	0
Security's volatility	1
Proportion of informed traders	5%
Uninformed traders' probability to buy, sell and hold	33.3% for each
Risk-free interest rate	1%
Volatility in informed traders' value assessment	1%
Market size	100.00
Security held by informed traders	N(30.15)
Security held by uninformed traders	N(15.15)
Maximum security held by the market maker (risk-taking willingness)	120.00
Market makers' risk tolerance (technical parameter for risk sensitivity)	1.00

Source: Author's elaboration.

The market maker's risk sensitivity and risk tolerance relative to issued securities are crucial model inputs, influencing reactions to risk and expected returns. Risk sensitivity, technically set at a standard value of 1, and risk tolerance, indicating the market maker's capacity to assume additional market risk (standard value at 1.2 or 20% more risk), are foundational. The proportion of informed traders, set at 5% as standard, represents their share among all traders, impacting market dynamics significantly.

The initial security value is set at a standard of 100, with its path influenced by parameters defining its fundamental value distribution, assumed to follow geometric Brownian motion with a standard normal distribution. The risk-free interest rate, set initially at 1%, affects expected returns. Uninformed traders' actions, governed by the probability of trading versus holding, with a standard action probability set at 66.6%, also play a critical role.

Trading behaviour, crucial for understanding market dynamics, is modelled through a stochastic process for both trader types. Informed traders are assumed to trade a higher volume, reflecting their access to superior information or institutional status. The study explores how variations in these parameters influence the bid-ask spread, with simulations providing insights into the impact of dealer and trader behaviours and market features on market liquidity and spread dynamics. The sequential model progression, depicted in an accompanying graph, facilitates a structured analysis over 50 periods.

4. RESEARCH RESULTS

We can distinguish various types of impact on the bid-ask spread. These are the following: effects from the dealer market; effects from the security market; effects from the trader; and information asymmetry.

This paper introduces an innovative approach to examining the impact of various factors under different assumptions and initial parameters. By analyzing these factors across multiple scenarios, the complexity of the model allows for the exploration of multidimensional outcomes, capturing multiplier effects and interconnections. In the benchmark scenario, we assume the dealer has a unit risk sensitivity, a willingness to take on risks 20% greater than the issued securities, all securities are initially sold to the market maker, informed traders constitute 30% of the market, and uninformed traders have equal chances of buying, selling, or holding in each period.

Different scenarios were employed to explore these interconnected effects, summarized in Table 1. While Table 1 presents scenarios analyzed for each parameter, additional relevant scenarios were considered as needed.

Table 1. Basic scenarios for analysing the parameters' impact on the spread

	Price path	Trading activity of uninformed	Volatility	Return
Benchmark	Random walk — N(0,1)	Equal probability for buy, sell and hold	1	0.01
Bull market	Stochastic process for the market is N(1,1)	Equal probability for buy, sell and hold	1	0.01
Bear market	Stochastic process for the market is N(-1,1)	Equal probability for buy, sell and hold	1	0.01
Active traders	Random walk — N(0,1)	44.5% for both buy and sell and 1% for hold	1	0.01
Passive traders	Random walk — N(0,1)	25% for both buy and sell and 50% for hold	1	0.01
High volatility	Random walk — N(0,1)	Equal probability for buy, sell and hold	3	0.01
Low volatility	Random walk — N(0,1)	Equal probability for buy, sell and hold	0.5	0.01
Low return	Random walk — N(0,1)	Equal probability for buy, sell and hold	1	0.001
High return	Random walk — N(0,1)	Equal probability for buy, sell and hold	1	0.1

Source: Author's elaboration.

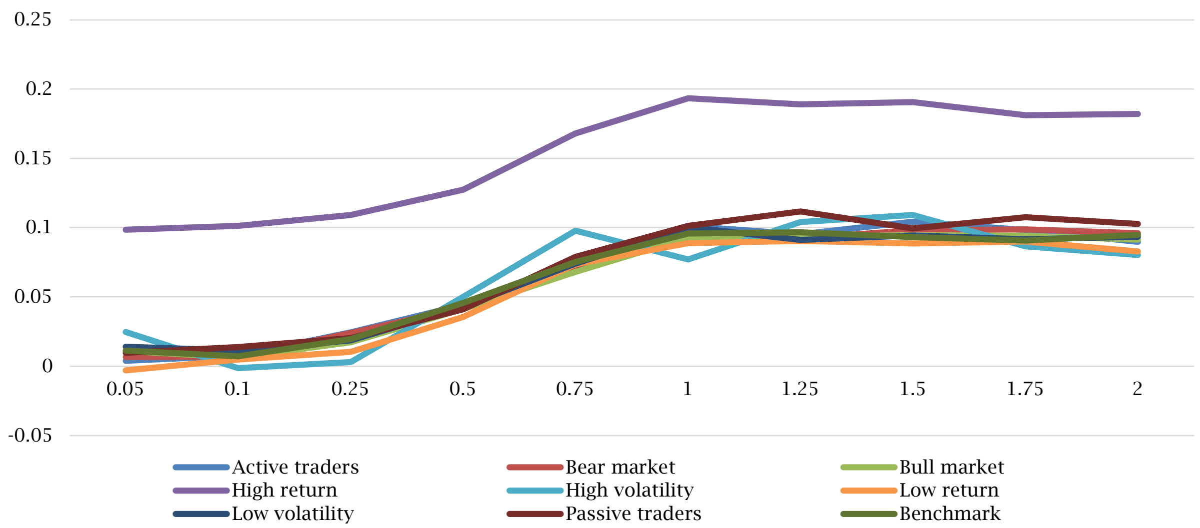
The results show the average bid-ask spread for 50 periods at different values and on different initial assumptions, therefore, we are able to detect the spread impact of the factors. As it has been shown, the bid-ask spread is a valid and popular proxy for market liquidity, therefore, we can infer that those effects impact liquidity which is inversely proportional to the spread effects thus whenever the spread increases, the liquidity decreases and vice versa.

4.1. Dealer market effects

Dealers determine the price of securities based on their risk sensitivity, unhedged risks, and willingness to take risks. This risk appetite reflects the maximum unhedged risk a market maker is prepared to accept, affecting bid-ask spreads symmetrically for both long and short positions. Essentially, the principle that higher returns come with higher risks applies here; as market makers' risk willingness increases, so do the spreads to accommodate larger trader demands, indicating market depth through the risk willingness parameter.

Scenario analysis reveals that spreads typically widen with high return expectations, while passive trader scenarios result in less liquidity and wider spreads due to decreased trading interest. Simulation results suggest the impact of risk willingness on bid-ask spreads varies with market size; larger markets see more significant changes in spreads with adjustments in risk willingness. This outcome aligns with assumptions about consistent trading activity among investors, suggesting a realistic portrayal of market dynamics.

Figure 3. The impact of risk-taking willingness on the bid-ask spread with various scenarios

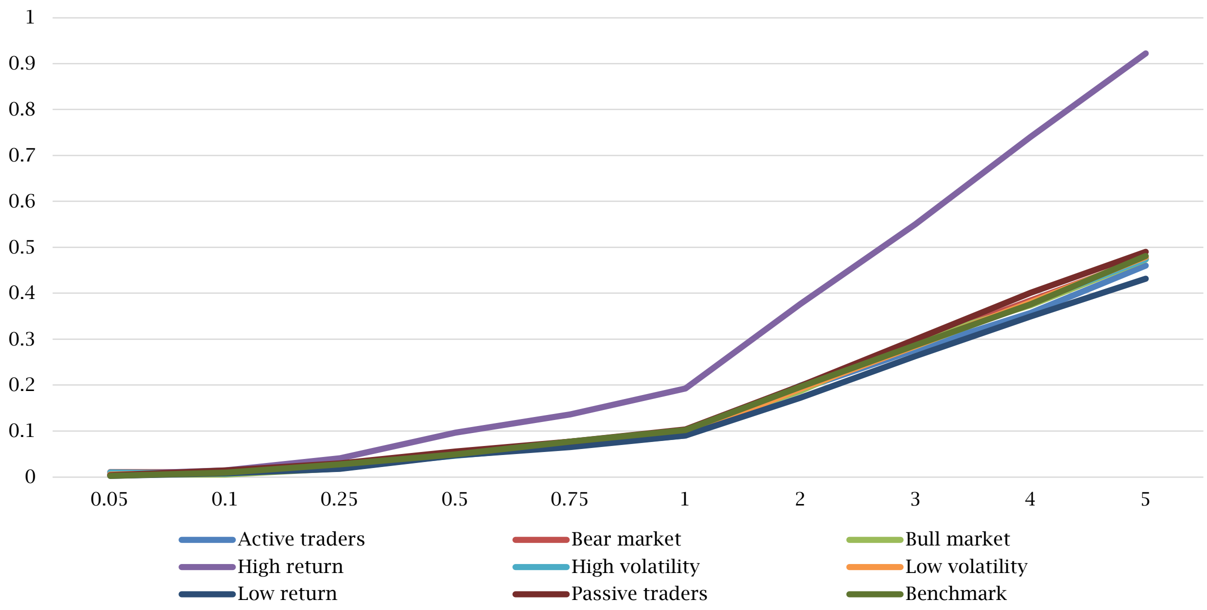


Source: Author's elaboration.

The risk sensitivity of the dealer also influences the bid-ask spread. To contain these effects a merely technical parameter is considered as it is supposed to reflect the market competition, market concentration, client's access to the dealers, credit risk, counterparty credit risk and so on. The results confirm that larger risk sensitivity results in a wider spread. It is important to emphasize that it is strictly assumed that the risk-taking willingness and risk sensitivity of the dealer are independent of one another.

Every factor affects the spread impact of the risk sensitivity. Further simulation results confirm that risk-taking willingness has an outstanding multiplier effect on the spread impact of risk sensitivity which are two very close concepts but in this model are assumed and handled as independent features.

Figure 4. The impact of risk sensitivity on the bid-ask spread with various scenarios



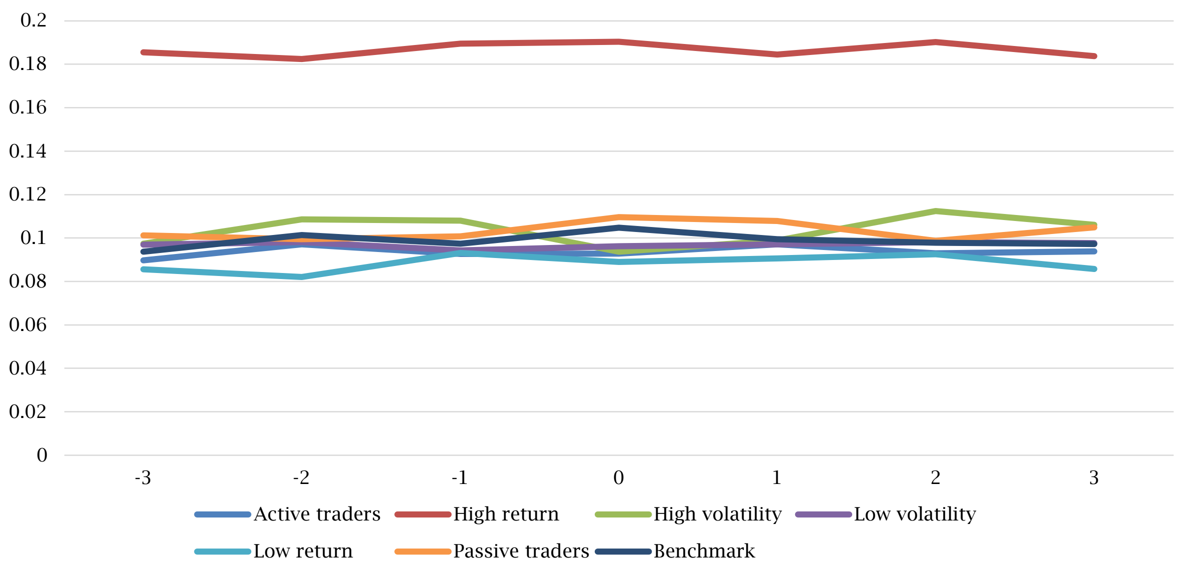
Source: Author's elaboration.

4.2. Market effects

Other market elements can also affect the spread example given: the path of the fundamental value of the security, its volatility and the risk-free interest rate. The prior means the direction of development in the fundamental price, in other words, whether the price goes up or down. In the simulation, the path of the value is determined by a stochastic process, i.e., the change in the value is a random number from a normal distribution (standard normal distribution in the benchmark scenario). In the simulation, we applied different numbers for the mean of the distribution, therefore, we could determine the path of the value.

According to our simulation, the path of the fundamental value has no significant impact on the liquidity impact however different impacts have been detected in different scenarios.

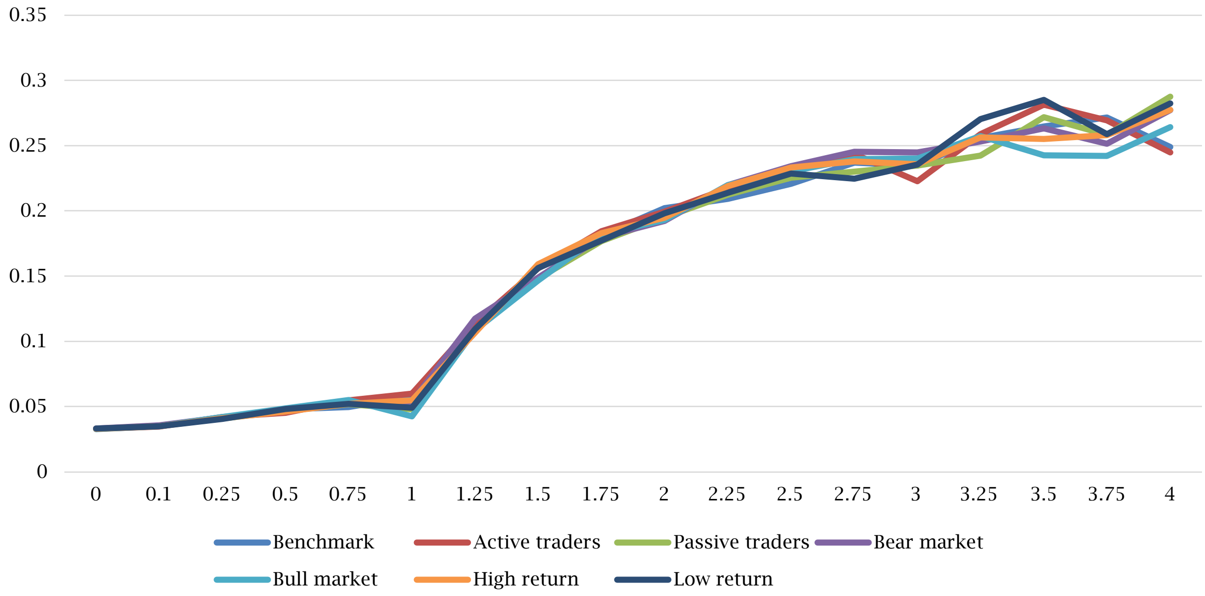
Figure 5. The impact of value's path on the bid-ask spread with various scenarios



Source: Author's elaboration.

The volatility of the security is also an important element for the liquidity of the market. The more volatile the market the wider the spread is. Volatility is a great proxy for the riskiness of a security, therefore, we can imply that the riskier the security the higher the spread is. In practice, the volatility determines the applied haircut on the security, which can impact the security's liquidity. The higher the volatility, the higher the resulting applied haircut. This reduces the security's desirability as collateral and thus decreases the liquidity.

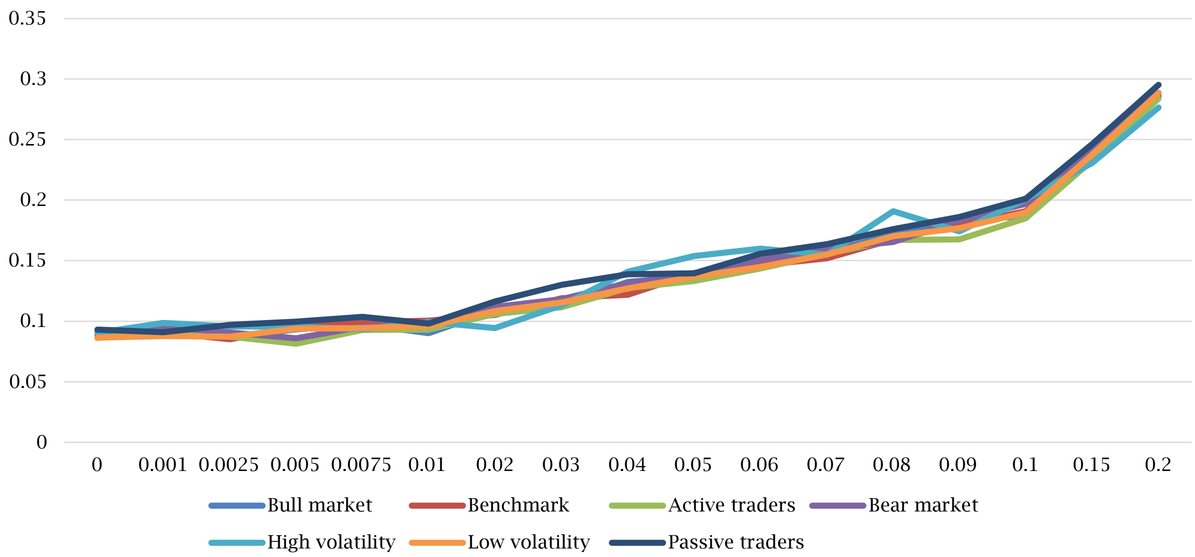
Figure 6. The impact of security's volatility on the bid-ask spread with various scenarios



Source: Author's elaboration.

The risk-free interest rate affects the expected rate of return for the market maker. As the model confirms our expectations higher risk-free interest rate results wider spread in the market, therefore, we can conclude that the market liquidity is lower. An increase in the risk-free interest rate increases the financing cost of the market maker and throughout the yield searching the market maker would look for other investment opportunities without increasing it is on profitability. This is why we can say one of the most important roles of the risk-free interest rate is the benchmark role which is getting more emphasized in contemporary times for monetary transmission mechanisms. Monetary policy can influence the risk-free interest rate which can determine the liquidity of the markets and, therefore, maintain stability for interbank collateral securities markets.

Figure 7. The impact of risk-free interest rate on the bid-ask spread with various scenarios



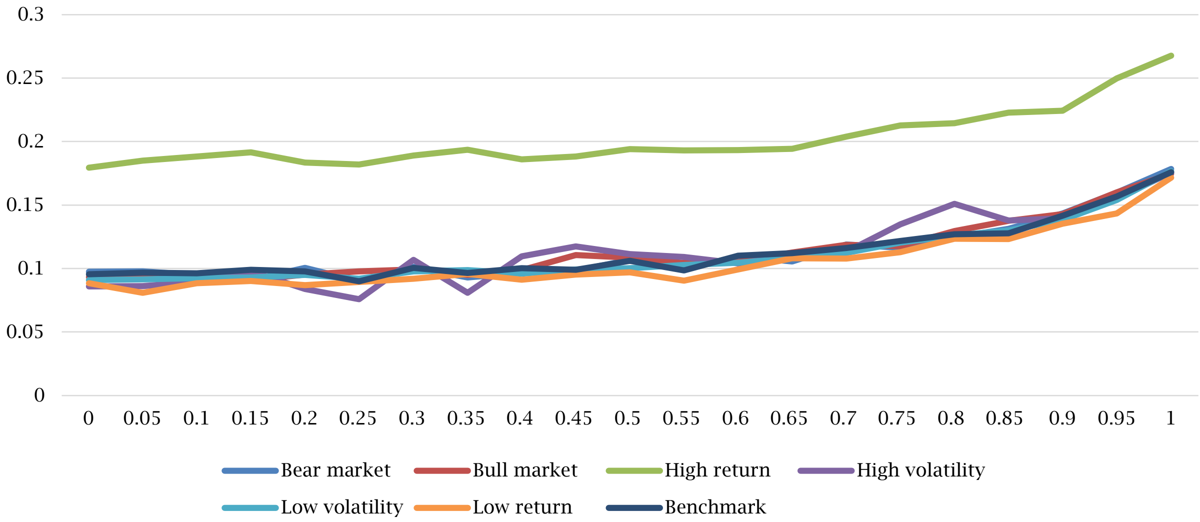
Source: Author's elaboration.

4.3. Traders' activity

The trading activity affects the bid-ask spread and, thus, the liquidity of the market. Trading activity means the trading probability of uninformed traders in each sequence which remains stable higher probability, it would be easier to find someone else who also wants to trade.

The path of the fundamental value does not seem to affect the way the activity affects the spread. However, the proportion of informed traders can have an impact on the effect of activity. The decisions of informed investors are determined by the price, therefore, the more uninformed traders the higher the impact is on the spread. But it is true for high activity and there is no difference when the uninformed traders are passive. In the case of passive traders, they would hold their position which would result in the same activity in any scenario as the only trades are done by informed investors. Figure 8 shows how the spread is influenced when the probability of holding increases.

Figure 8. The impact of trading activity on the bid-ask spread with various scenarios

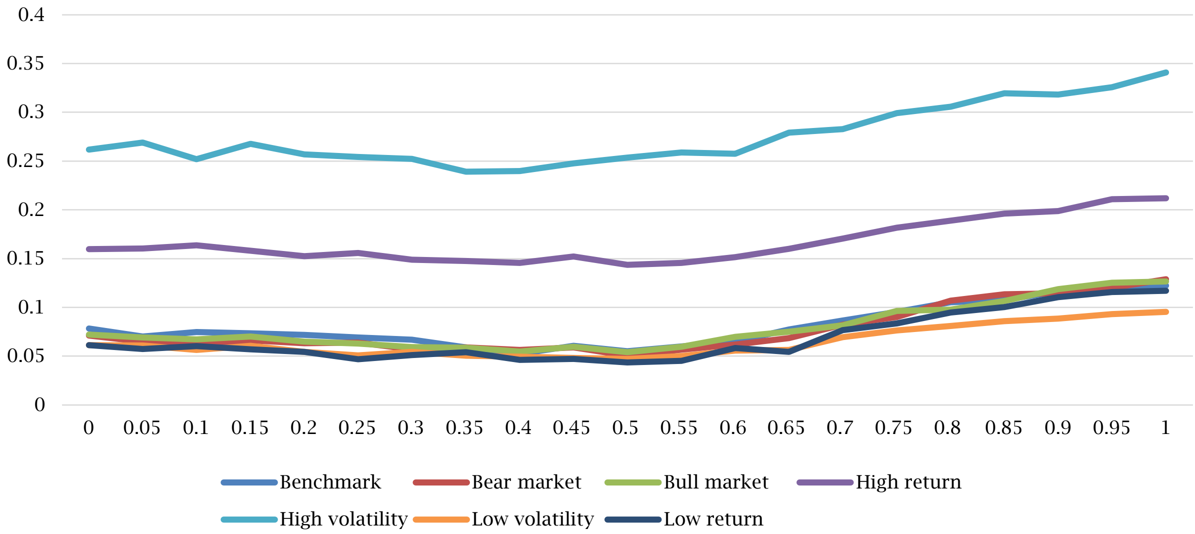


Source: Author's elaboration.

The adjusted model was able to help us understand how herd behaviour would affect the spread. In this case, the probability of buying is different from the probability of selling and for technical simplicity keeping a position is not allowed for uninformed traders. The probability of buying is ζ while the probability of selling is $(1 - \zeta)$. In general, the increasing probability of buying reduces the spread until the probability is 55–60%. At first sight, it might be interesting that the lowest spread is not at equal chances for buying and selling but the result is determined by the assumption made about the dealer market. The dealer holds while unable to hedge the issued securities in the initial period so the dealer's starting position is net long, therefore, equal chances would on average keep this exposure in its balance sheet. A little bit higher probability of buying helps the market maker to close its net long position. The too-large probability of buying means that the market maker has to maintain an even higher short position, therefore, the spread is wider when the selling probabilities are higher. The impact of selling and buying probabilities is asymmetric because the short position of the investors is not allowed in the model.

The proportion of informed dealers would influence the spreading impact of the trading activity because only uninformed investors' deal is described as a stochastic process while informed traders act with information in hand.

Figure 9. The impact of trading activity with no possibility of position keeping on the bid-ask spread with various scenarios



Source: Author's elaboration.

4.4. Information asymmetry

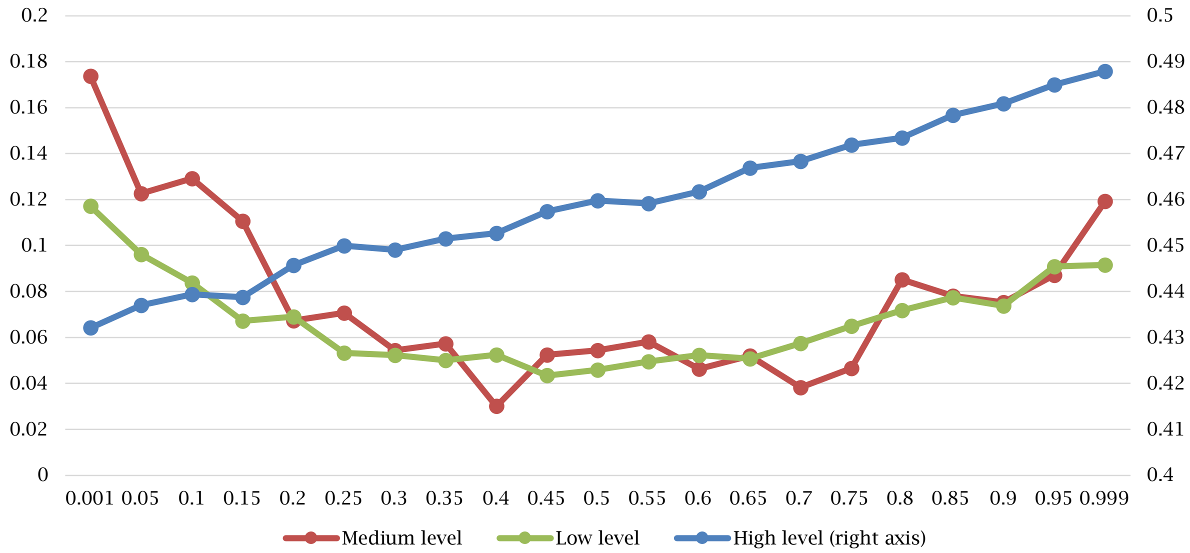
Information asymmetry arises because the market maker is not aware if it makes a deal with informed or uninformed traders. By adjusting the model, we can analyse how the different degrees of information asymmetry can determine the spread. Therefore, we can distinguish three types of scenarios for different degrees of information asymmetry.

- High level of information asymmetry: The market maker is not aware of the true fundamental value of the security while the informed traders know the proper value of the security. This is assumed in various papers (Glosten & Milgrom, 1985; Kyle, 1985; Easley & O'Hare, 1987).
- Medium level of information asymmetry: Market makers know the density function for the fundamental value of the security. So, this stochastic process is a normal distribution where the mean is the fundamental value, and the standard deviation is half of the security's standard deviation. The informed traders know the proper value of the security.
- Low level of information asymmetry: Market makers and informed traders know the fundamental value as a density function. This scenario seems to be the most realistic.

Informed traders can cause information asymmetry and induce adverse selection costs that make the dealer set wider bid and ask prices. The simulation results confirm that the larger proportion of informed traders results in wider spreads in case of high information discrepancies. Therefore, one of the spread's compositions is a premium that the market maker demands for trading with informed traders. The trading activity of uninformed investors can change the spread impact of information asymmetry. In the case of passive or non-trading uninformed traders, the increasing proportion of informed traders does not increase the average width of the spread as it appears from the graph below. It is caused by the trading structure, as the trading book of the dealer lists only informed traders because the uninformed traders are inactive. So, in spite of the low proportion of informed traders, all of the deals managed by the market maker are done with informed traders and most probably it is lower in quantity.

At the medium and low degrees of information asymmetry, the proportion of informed traders decreases the spread until a point, and then it increases. It is due to the fact informed traders help the market maker to adjust its balance sheet whenever it is needed, therefore, they help to maintain the fair price of the market. This result is closely related to Cornell and Sirri (1992) and Coling-Dufresne and Fos (2015).

Figure 10. The impact of informed traders' proportion on the bid-ask spread with various scenarios



Source: Author's elaboration.

4.5. Robustness check, model validity

To check the robustness of the results, empirical confidence intervals were calculated for every case. A confidence interval is a parameter estimation of a population calculated from empirical data. Should the related known or observed value for the simuland be within the confidence interval the model is accepted as true for the parameter in question. Of course, provided that it was calculated from the model executions, or within some acceptable tolerance of the confidence interval's endpoints (Petty, 2012).

The confidence interval for the population is calculated in Eq. (10).

$$\left[\bar{X} - t_{N,\alpha}\frac{\sigma}{\sqrt{n}}, \bar{X} + t_{N,\alpha}\frac{\sigma}{\sqrt{n}}\right] \quad (10)$$

where, $\bar{X}$ is the sample mean, σ is the sample standard deviation, n is the sample size and $t_{N,\alpha}$ is a parameter that is derived from Student's t distribution at N - 1 degrees of freedom at α confidence level.

The confidence interval was calculated on a 95% confidence level. Therefore, the calculated confidence intervals are constructed to contain 95% of the population parameter.

The confidence intervals are measured to be stable over different parameters and different parameters' values are expected for high and low standard deviation scenarios. The confidence intervals' range was calculated for 0.009 which is less than 10% of the output average. It is more than doubled for the high volatility scenarios and half of it was measured for the low volatility scenarios. Therefore, the outputs of the model are robust and significant. We cannot confirm the robustness and significance of the volatility scenarios however, we need to be permissive for these cases as volatility is the key essence of this variation, which will endogenously result in higher confidence intervals by increasing the volatility of the output.

5. DISCUSSION

The theoretical model utilized in this paper provides four important economic implications. These are related to the efficiency of the regulation, the limitations of micro- and macroprudential regulation, central bank policy and the commonality in liquidity.

The model described in this paper helps us to understand how the behaviour and financial position of financial institutions (i.e., market makers) contribute to market conditions. Therefore, important implications can be deducted focusing on financial stability throughout micro- and macroprudential regulation. Overall, we can imply that microprudential regulation can help us maintain stability on the level of institutions and the market. However, intensifying regulation would result in more stable financial institutions but (due to the institutions' declining risk-taking willingness and increasing risk sensitivity) the regulation might have a negative influence on market liquidity.

The results regarding the degree of information asymmetry can help us to understand one of the reasons why the regulations have different impacts on different asset markets.

As per the above-mentioned factors, we can conclude that there is an optimal level of regulation because too liberal rules would lead to instability on both institutional and market levels, while too rigorous regulation would no doubt be beneficial for continued institutional stability, yet, on the other hand, it would have a negative impact on the level of the market. The goal of macroprudential regulation is to find the optimum application of microprudential rules.

The model results provide essential takeaways regarding central bank policy as well. A risk-free interest rate has a direct effect on market liquidity because of the profitability of the market makers (this is because yield-searching market makers can turn their attention to risk-free assets instead of providing liquidity). But monetary policy can also affect the risk sensitivity of the market makers if the central bank communicates that it is ready to step in as a dealer of last resort whenever the market needs it. In this case, dealers become less risk-sensitive so it results in tighter spreads. If the market knows that the central bank is ready to act as a dealer of last resort, the market makers would also increase the maximum risk they are willing to take because they are aware of the further possibilities to adjust their risk position via the central bank's asset purchasing program.

Liquidity of different financial assets are cointegrated as many studies have confirmed (Chordia et al., 2001; Brockman & Chung, 2006; Koch et al., 2016; Karolyi et al., 2011). The reason behind this well-documented phenomenon is that the liquidity of financial assets is provided by the same financial institutions (dealers) and their capability to provide market liquidity depends not just on market-specified factors but also on dealer-specified factors.

6. CONCLUSION

In this paper, a new microeconomic model for market makers has been introduced with realistic assumptions. In addition to the financial literature, the basic assumption of the paper is not just that the market maker is not only capable of adjusting the price but also the spread as well on its risk position. This approach is based on a basic concept of finance: more risk means a greater expectation of returns. It is also assumed that short- and long-term risks are symmetric. In other words, the greater the risk the greater the spread is in absolute terms. On the contrary from the majority of literature, we also assume that the dealer is aware of the basic value of the security, while the market provider is determined not to sell the security under that given price as well as not to buy the security above the awarded price. It is also assumed that the market maker's goal is to persuade the traders to modify the dealer's balance sheet in order to push the traders to sell should the dealer be net short and vice-versa. For the previously explained assumption in our analysis, we utilize a concave function for the bid and a convex function for the ask price.

As the output of the three-agent Monte Carlo simulation showed, the liquidity of financial markets can be considered as a rather complex phenomenon. The liquidity impact of the factors may differ from the initial positions and the applied assumptions (e.g., regulation). Generally, an increase in risk-taking willingness, risk sensitivity and market size (quantity of issued securities) would make the spread wider but these impacts on liquidity are not joint and numerous for every scenario. The paper also distinguishes low, medium and high levels of information asymmetry. The simulation results confirm that the larger proportion of informed traders results in wider spreads at a high level of information asymmetry while at medium and low degrees of information asymmetry, the proportion of informed traders increases the liquidity until a point then it decreases. This result can describe the theoretical background of some empirical works which surprisingly find that liquidity increases when there is more active informed trading.

Initial position, trading activity, trading volume and path of fundamental value do not have such a clear way to affect. The impact can be smaller, larger, convex or concave depending on the underlying initial assumptions. It indicates that market movements generally do not significantly alter the bid-ask spread and that liquidity impacts vary depending on the scenario. Market volatility is shown to increase the bid-ask spread by a decreasing magnitude, with a moderate impact on liquidity. Trading activity decreases dynamically, also affecting liquidity moderately. The willingness to take risks increases by a decreasing magnitude with only a slight impact on liquidity, while risk sensitivity increases exponentially, significantly affecting liquidity. The risk-free interest rate's dynamic increase has a moderate effect on liquidity. Information asymmetry's impact on the bid-ask spread is described through a U-shaped graph or a dynamic increase, with a moderate liquidity impact.

Four important economic implications have been addressed as a consequence of the results. These are related to the efficiency of the regulation, the limitations of micro- and macroprudential regulation, central bank policy and the commonality in liquidity.

The paper is based on a stochastic theoretical model that can help to understand real-world phenomena. The applied parameters and dynamism included in the parameter set can help us further investigate real market situations.

In this study, while the simulation is dynamic, certain parameters are held constant over time, which presents a limitation. Adjusting these parameters dynamically could provide a deeper understanding of the outcomes. Additionally, as the model presented is theoretical, future research could involve empirically estimating these parameters and investigating the relationships empirically.

REFERENCES

Amihud, Y., & Mendelson, H. (1980). Dealership market: Market-making with inventory. *Journal of Financial Economics*, *8*(1), 31–53. https://doi.org/10.1016/0304-405X(80)90020-3

Amihud, Y., & Noh, J. (2020). Illiquidity and stock returns II: Cross-section and time-series effects. *The Review of Financial Studies*, *34*(4), 2101–2123. https://doi.org/10.1093/rfs/hhaa080

Bagehot, W. (1971). The only game in town. *Financial Analysts Journal*, *27*(2) 12–14, https://doi.org/10.2469/faj.v27.n2.12

Baldauf, M., & Mollner, J. (2020). High-frequency trading and market performance. *The Journal of Finance*, *75*(3), 1495–1526. https://doi.org/10.1111/jofi.12882

Bélyácz, I., & Szász, E. (2014). A pénzügyi rendszer válsághajlamának mélyebb gyökereiről. Gondolatok a likviditási paradoxon kialakulásáról [About the deeper roots of the financial system's propensity for crisis. Thoughts on the emergence of the liquidity paradox]. *Köz-Gazdaság*, *9*(1), 82–100. https://www.retp.eu/index.php/retp/article/download/511/470

Brockman, P., & Chung, D. Y. (2006). Index inclusion and commonality in liquidity: Evidence from the Stock Exchange of Hong Kong. *International Review of Financial Analysis, 15*(4–5), 291–305. https://doi.org/10.1016/j.irfa.2005.09.003

Brunnermeier, M. K., & Pedersen, L. H. (2009). Market liquidity and funding liquidity. *Review of Financial Studies*, *22*(6), 2201–2238. https://doi.org/10.1093/rfs/hhn098

Chordia, T., Roll, R., & Subrahmanyam, A. (2001). Market liquidity and trading activity. *The Journal of Finance, 56*(2), 501–530. https://doi.org/10.1111/0022-1082.00335

Chuliá, H, Mosquera-López, S., & Uribe, J. M. (2023). Nonlinear market liquidity: An empirical examination. *International Review of Financial Analysis*, 87, Article 102532. https://doi.org/10.1016/j.irfa.2023.102532

Collin-Dufrense, P., & Fos, V. (2015). Do prices reveal the presence of informed trading? *The Journal of Finance*, *70*(4), 1555–1582. https://doi.org/10.1111/jofi.12260

Copeland, T. E., & Galai, D. (1983). Information effects on the bid-ask spread. *The Journal of Finance*, *38*(5), 1457–1469. https://doi.org/10.1111/j.1540-6261.1983.tb03834.x

Cornell, B., & Sirri, E. R. (1992). The reaction of investors and stock prices to inside trading. *The Journal of Finance*, *47*(3), 1031–1059. https://doi.org/10.1111/j.1540-6261.1992.tb04004.x

Coughenour, J. F., & Saad, M. M. (2004). Common market makers and commonality in liquidity. *Journal of Financial Economics, 73*(1), 37–69. https://doi.org/10.1016/j.jfineco.2003.05.006

Das, S. (2005). A learning market-maker in the Glosten-Milgrom model. *Quantitative Finance, 5*(2), 169–180. https://doi.org/10.1080/14697680500148067

Easley, D., & O'Hare, M. (1987). Price, trade size, and information in securities markets. *Journal of Financial Economics*, *19*(1), 69–90. https://doi.org/10.1016/0304-405X(87)90029-8

Glosten, L. R., & Milgrom, P. R. (1985). Bid, ask and transaction prices in a specialist market with heterogeneously informed traders. *Journal of Financial Economics*, *14*(1), 71–100. https://doi.org/10.1016/0304-405X(85)90044-3

Gromb, D., & Vayanos, D. (2002). Equilibrium and welfare in markets with financially constrained arbitrageurs. *Journal of Financial Economics*, *66*(2–3), 361–407. https://doi.org/10.1016/S0304-405X(02)00228-3

Grossman, S. J., & Miller, M. H. (1988). Liquidity and market structure. *The Journal of Finance, 43*(3), 617–633. https://doi.org/10.1111/j.1540-6261.1988.tb04594.x

Harris, L. (1991). *Liquidity, trading rules, and electronic trading systems.* New York University Salomon Center.

Hasbrouck, J., & Seppi, D. J. (2001). Common factors in prices, order flows, and liquidity. *Journal of Financial Economics, 59*(3), 383–411. https://doi.org/10.1016/S0304-405X(00)00091-X

Jylha, P. (2016). Does funding liquidity cause market liquidity? Evidence from a quasy-experiment. http://doi.org/10.2139/ssrn.2651088

Karolyi, G. A., Lee, K.-H., & van Dijk, M. A. (2011). Understanding commonality in liquidity around the world. *Journal of Financial Economics*, *105*(1), 82–112. https://doi.org/10.1016/j.jfineco.2011.12.008

Koch, A., Ruenzi, S., & Starks, L. (2016). Commonality in liquidity: A demand-side explanation. *The Review of Financial Studies, 29*(8), 1943–1974. https://www.jstor.org/stable/43866073

Kyle, A. S. (1985). Continuous auctions and insider trading. *Econometrica*, *53*(6), 1315–1335. https://doi.org/10.2307/1913210

Mehrling, P. (2014). *Why central banking should be re-imagined* (BIS Paper No 79). Bank for International Settlements (BIS). https://ssrn.com/abstract=2504713

O'Hara, M., & Oldfield, G. (1986). The microeconomics of market making. *Journal of Financial and Quantitative Analysis*, *21*(4), 361–376. https://doi.org/10.2307/2330686

Petty, M. D (2012). Calculating and using confidence intervals for model validation. In *Fall Simulation Interoperability Workshop 2012* (pp. 37–45). Simulation Interoperability Standards Organization (SISO).
Sarr, A., & Lybek, T. (2002). *Measuring liquidity in financial markets* (IMF Working Paper No. WP/02/232). International Monetary Fund (IMF). https://doi.org/10.5089/9781451875577.001
Schwartz, R. A., Francioni, R., & Weber, P. (2020). Market liquidity: An elusive variable. *Journal of Portfolio Management, 46*(8), 7–26. https://doi.org/10.3905/jpm.2020.1.174
Sommer, P., & Pasquali, S. (2016). Liquidity — How to capture a multidimensional beast. *The Journal of Trading, 11*(2), 21–39. https://www.pm-research.com/content/iijtrade/11/2/21
Szunke, A. (2014). The role of financialization in banking sector instability. *Journal of Economics & Management, 16*, 98–111. https://shorturl.at/DchrR
Treynor, J. L. (1987). The economics of the dealer function. *Financial Analysts Journal*, *43*(6), 27–34. https://doi.org/10.2469/faj.v43.n6.27
Váradi, K. (2012). Volt-e likviditási válság? Volatilitás és likviditás kapcsolatának vizsgálata [Was there a liquidity crisis? Analysis the relationship between volatility and liquidity]. *Financial and Economic Review,* (Special issue), 69–78. https://unipub.lib.uni-corvinus.hu/1036/1/69-78-ig-varadi-kata.pdf
Wang, T. (2014). *Empirical analysis of sequential trade models for market microstructure* [Doctoral dissertation, University of North Carolina]. https://doi.org/10.17615/1pr9-fm83
Wei, S.-J. (1994). *Anticipation of foreign exchange volatility and bid-ask spreads* (NBER Working Paper No. 4737). National Bureau of Economic Research (NBER). https://doi.org/10.3386/w4737