TOXICITY ON THE LIQUIDITY OF DI AND COMMERCIAL DOLLAR FUTURES CONTRACTS

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ABSTRACT

The aim of this paper was to analyze the impact of the order flow toxicity – Volume-Synchronized Probability of informed trading (VPIN) – of DI and Commercial Dollar futures contracts traded on Brasil Bolsa Balcão (B3) on the market liquidity of these assets – bid-ask spread. It is argued that the asymmetry of information between the agents participating in a transaction generates an imbalance between the orders placed, which affects the securities liquidity. Empirically, intraday data of DI and Commercial Dollar futures contracts traded on B3 from September 2018 to August 2019 were used to estimate a multiple linear regression model and analyze this relationship. The results showed a significant and positive relationship between VPIN and bid-ask spread in the models estimated for both contracts. Thus, we may conclude that the VPIN is one of the factors that affect liquidity in DI and Commercial Dollar Futures negotiations, that is, the higher the orders flow toxicity (higher degree of informational asymmetry), the lower the securities liquidity.

Keywords: Toxicity. VPIN. Market Liquidity. Bid-Ask Spread.

TOXICIDADE DOS FLUXOS DE ORDENS SOBRE A LIQUIDEZ DOS CONTRATOS FUTUROS DE DI E DÓLAR COMERCIALORDER FLOW

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RESUMO

O objetivo deste estudo foi analisar o impacto da toxicidade dos fluxos de ordens – *Volume-Synchronized Probability of informed trading* (VPIN) – dos contratos futuros de DI e de Dólar Comercial negociados na Brasil Bolsa Balcão (B3) sobre a liquidez de mercado desses ativos – representada pelo *bid-ask spread*. Argumenta-se que a assimetria de informações entre os agentes participantes de uma transação gera um desequilíbrio entre as ordens lançadas, o que afeta a liquidez dos títulos. Empiricamente, utilizaram-se dados intradiários de contratos futuros de DI e Dólar Comercial negociados na B3 de setembro de 2018 a agosto de 2019 para estimar um modelo de regressão linear múltipla e analisar esse relacionamento. Os resultados encontrados mostraram que a relação entre a VPIN e o *bid-ask spread* foi significante e positiva nos modelos estimados para ambos os contratos. Dessa forma, concluiu-se que a VPIN é um dos fatores que impactam a liquidez nas negociações de DI Futuro e Dólar Comercial Futuro, ou seja, quanto maior a toxicidade do fluxo de ordens (maior grau de assimetria informacional), menor a liquidez dos títulos negociados.

Palavras-Chave: Toxicidade. VPIN. Liquidez de Mercado. *Bid-Ask Spread*.

1 INTRODUCTION

Market liquidity and its relationship with asset returns have been the subject of research since the mid-1980s (Amihud & Mendelson, 1986; Jun, Marathe & Shawky, 2003; Blau, Griffith & Whitby, 2018). In addition to its relationship with returns, the liquidity of securities is important because it strengthens markets, reduces issuance and transaction costs, and increases the number of participants in transactions. Therefore, it is critical to understand the factors impacting the market liquidity of securities, such as transaction costs, market efficiency, the aftermarket trading and settlement system, market transparency, the broadening and diversification of the investor base, and the asymmetry of information present in trading (O'Hara, 2003; Li, Lambe & Adegbite, 2018; Yildiz, Van Ness B. & Van Ness R., 2019).

Information asymmetry occurs when there is an imbalance between the information that agents possess; that is, when there is an unbalance of information about a given transaction among its participants (some have more information than others). As Grossman and Stiglitz (1980) point out, there are informed and uninformed traders in the market – the degree of information differs among agents – and this aspect is reflected in the price of assets. Informed traders hold relevant information about the traded asset and can cause losses to their counterparts. An informed trade is one in which at least one side of the transaction has more information than the other. A market with a high proportion of informed trades in relation to uninformed ones is called "toxic." In addition, high toxicity in order flow entails the liquidation of assets by traders, thus decreasing market liquidity (Easley, Prado, & O'Hara, 2012).

The influence of order flow toxicity on liquidity has encouraged several theoretical-empirical studies regarding market microstructure, such as Easley, Kiefer, O'Hara e Paperman (1996), Easley, Hvidkjaer e O'Hara (2002), Easley, Engle, O'Hara e Wu (2008), Easley, Prado e O'Hara (2011) and Easley et al. (2012), all of whom were searching for a way to identify informational asymmetry in markets. In turn, this has basically resulted in the proposition of two measurement models or indicators: (i)The Probability of Informed Trading (PIN) by Easley et al. (1996), which seeks to estimate the probability of transactions based on private information occurring in a given period, from a maximum likelihood function; and (ii) the Volume-Synchronized Probability of Informed Trading (VPIN), by Easley et al. (2011), which directly measures the degree of toxicity of order flows.

In studies on Brazilian stock market microstructure, the following topics have been addressed: (i) the liquidity-return relationship of stocks (Correia, Amaral & Bressan, 2008; Machado & Medeiros, 2011; Perobelli, Famá & Sacramento, 2016); (ii) the potential effects of hiring market makers on stock market liquidity (Perlin, 2013); (iii) the impact of the level of order flow toxicity on stock returns in the Brazilian stock market (Siqueira, Amaral & Correia, 2017); and (iv) the effect of toxicity in the futures market (Barbosa, 2014; Ribeiro, Souza & Moraes, 2020), which, according to Andrade (2015), has a number of specificities, such as daily adjusted value, which, in turn, supply liquidity to the market.

Among the various assets traded in the Brazilian futures market, we highlight the One-day Interbank Deposit Futures (from now on, DI Futures) and U.S. Dollar Spread Futures (from now on, U.S Dollar Futures). The DI Futures are the most traded asset in the Brasil Bolsa Balcão (B3) and refers to the interest rate of the CDI (Interbank Deposit Certificate) that the market estimates for the day of maturity of the contract. Due to its hedging function against oscillations in the interest rate of financial contracts, it plays a crucial role in investments. In turn, the U.S. Dollar Spread Futures are used for foreign exchange transactions between banks, financial institutions, and large corporations.

For example, Garcia and Urban (2004) argue that exchange and interest rates, from the macroeconomic perspective, are the most relevant variables to define macroeconomic aggregates, such as investments, consumption, imports, and exports. From the microeconomic perspective, the exchange rate is decisive for the behavior of entrepreneurs and consumers because it influences the commercialization of imported and exported goods and services, making the formation process of these rates essential for market participants. Moreover, the financial volume traded in DI Futures contracts has been significant in the last five years, exceeding US$50 trillion. In 2018, for example, more than US$8.7 trillion were traded in DI Future contracts, the largest amount traded in this market. In that same year, the financial volume of U.S. Dollar Futures contracts, the second most traded asset on the B3 futures market, totaled more than US$4.5 trillion and exceeded US$9.5 trillion over the past five years (B3, 2022).

Whether it is for its hedge function, which allows fixing the price of the asset in order to reduce or eliminate the risk of unwanted price variation or the possibility of speculation, understanding the influence of order flow toxicity on liquidity in the Brazilian futures market is paramount, especially from the microeconomic perspective, to the extent that it helps companies and investors to make investments decisions. Martins and Paulo (2016) state that insider trading is illegal in Brazil. Nonetheless, Barbedo, Silva and Leal (2009), Martins, Paulo and Albuquerque (2013) and Martins and Paulo (2014) have found empirical evidence suggesting its existence in the Brazilian stock market. This article considers the harmful effect of asymmetry on relevant variables for companies' and investors' decisions, such as risk, return, liquidity, and cost of capital, and, therefore, aims to contribute to a better understanding of this phenomenon.

Considering the relevance of the DI and U.S. Dollar Futures markets at B3 and understanding the effect of information asymmetry on the market liquidity of the assets traded by them for the decision-making of companies and investors in financial and capital markets, this study aims to analyze the impact of the degree of toxicity of order flows of DI and U.S. Dollar Futures contracts traded at B3 on the market liquidity of these assets.

This study features four sections in addition to this introduction. The second section presents the theoretical framework for market microstructure, order flow toxicity, and market liquidity. The third describes the methodology by presenting the sample, the variables, and the estimated econometric models. The fourth outlines and discusses the results, and the fifth and final section presents the conclusions of this study.

2 THEORETICAL FRAMEWORK

2.1 Microstructure, Market Liquidity, and Information Asymmetry

Typically, market microstructure looks into how trading processes influence price volatility, market liquidity of assets, and other variables that impact the distribution of returns (Madhavan, 2000; Easley, Prado, O'Hara & Zhang, 2019). Along these lines, O'Hara (1995) has proposed models to understand the adverse selection problem faced by market makers, who are responsible for providing liquidity. To keep an efficient portfolio that compensates for the risk of keeping a non-efficient portfolio, market makers set different bid and ask prices, thus generating the spread (O'Hara, 1995).

There is no single concept to define market liquidity in the financial literature. Amihud e Mendelson (1986) defined it as the cost of immediate execution of a buy or sell order. According to them, liquidity is a crucial aspect of investment analysis and management, and there should be an inverse association between the liquidity of an asset and its return. According to Blau et al. (2018), market liquidity, generally defined as the ability to trade a security in a short period and at a low cost, is determined by multiple dimensions. In line with this perspective (but more broadly), Black (1971) proposes that a liquid market obeys the following criteria: (i) the existence of bid and ask prices for investors aiming at trading a small amount of the asset immediately; (ii) the spread must remain small; (iii) the transaction of large quantities of an asset may occur over a long period, at prices that do not diverge significantly from the current market price and the scarcity of special information; and (iv) large quantities can be traded immediately, but trading occurs upon the presence of a premium or discount that varies according to the size of the trade in question.

As a proxy for market illiquidity, Demsetz (1968) proposed the bid-ask spread, i.e., the difference between the highest bid and the lowest ask price of a given asset in the market. Over time, several studies in market microstructure, such as Amihud and Mendelson (1986), have adopted this measure to reflect the illiquidity of securities. Bernales, Cañón and Verousis (2018) consider that even after decades, the bid-ask spread remains a good proxy for illiquidity. In a simplified way, the spread can be explained by components such as order processing costs, inventory costs, and information asymmetry. In this sense, one of the strands of market microstructure is to analyze the informational content carried by security prices. As Akerlof (1970) demonstrated, informational asymmetry increases the spread of trades, consequently impacting asset returns.

Fama's (1970) analysis of the informational set reflected in asset prices boosted the search for understanding the impact of information asymmetry on asset trading. Copeland e Galai (1983), in studying the difference between the bid and the ask price set by a market maker, considered the informational component among market participants. Market makers transact with traders who hold private information and those who do not. Indeed, since they cannot distinguish between such traders, the spread represents a solution to compensate for possible losses associated with traders possessing more information. In other words, market makers can remain financially solvent by making gains with traders not possessing private information.

In the model proposed by Glosten e Milgrom (1985), the market participants are classified as uninformed and informed traders, given the information asymmetry between them. While uninformed traders have no relevant information about the value of the traded asset, informed traders sell their positions in the market if they receive bad news; likewise, they buy them (i.e., acquire positions in assets) if they have good news about their true value. Similarly, in the model developed by O'Hara (1995), informed traders seek to make their trades at the moment when their private information is most valuable. Thus, it is possible to identify clusters of transactions, that is, the moments in which more incoming orders occur.

As informational asymmetry is not a directly observable variable, proxies to analyze its effect on other variables (such as liquidity) have been developed in market microstructure studies. Among the proxies proposed in the literature are (i) PIN, proposed by Easley et al. (1996); and (ii) VPIN, proposed by Easley et al. (2011), which consists of a modified version of the first. These measures seek to quantify the probability of the existence of informed traders in a market, i.e., the toxicity level of the market.

The specialized literature argues that the impact of order flow toxicity (the imbalance between orders to buy and sell securities) on market liquidity possibly generates variations in asset prices and, consequently, in their returns (Rzayev & Ibikunle, 2019). In this sense, the following section discusses the main models for determining informational asymmetry: PIN and its evolution to VPIN.

2.2 Order Flow Toxicity

Easley et al. (1996) introduced the Probability of Informed Trading (PIN) model to measure order flow toxicity in markets. PIN stands out because it is obtained from the market's own trading data and is, therefore, a direct proxy of informational asymmetry. This measure has been widely used because it addresses various issues, such as information on the time elapsed between trades, electronic market order flow, stock splits, and asset prices. However, the adequacy of PIN to reflect informational asymmetry in trading has been questioned regularly, which is natural since PIN is a model that seeks to represent a phenomenon, and, therefore, cannot capture all related aspects (Duarte & Young, 2009; Easley, Hvidkjaer & O'Hara, 2010; Akay, Cyree, Griffiths & Winters, 2012).

In studying PIN as a model for estimating informational asymmetry, Duarte e Young (2009) pointed out that it is decomposed into two elements related to (i) private information; and (ii) liquidity. That is, transactions not conducted by informed traders are liquidity-seeking transactions. For the authors, PIN relies on abnormal imbalances in buy and sell orders to obtain the parameters, and such imbalances may result not from private information but changes in the demand for liquidity. This shows that the PIN component related to asymmetric information may not be priced, whereas the PIN component related to lack of liquidity is reasonably priced. The empirical evidence of Akay et al. (2012) corroborates the results pointed out by Duarte e Young (2009), who found that the PIN estimate can express changes in the demand for liquidity and the informational asymmetry present in the market.

Boehmer, Grammig and Theissen (2007) point out that although PIN is widely used in a wide range of applications in corporate finance and market microstructure, to estimate it, one must know the number of trades initiated by the buyer and seller. However, this information is not observable but deduced from the use of classification algorithms, which are imprecise. Thus, Boehmer et al. (2007) argue that incorrect order classification can result in incorrect PIN estimates.

In a study on the alleged use of private information in atypical operations with the common stocks of the JBS Company in the Brazilian capital market, Pordeus, Girão, and Duarte (2018) employed PIN to, among other objectives, identify whether it was possible to obtain abnormal returns (returns above the market average) through the parameters obtained using the PIN model adapted by Lin and Ke (2011). To this end, the authors analyzed the purchase and sale transactions of JBS common stocks carried out by insiders between January 2016 and December 2018. The results revealed that abnormal returns could not be obtained in the trades carried out in this period based on PIN and its parameters.

To correct PIN problems, such as not considering the volume of transactions and the time interval of trades, Easley et al. (2011) proposed a new model to estimate the probability of informed trades, called the Volume Synchronized Probability of Informed trading (VPIN). This metric is a real-time indicator of order flow toxicity and has some practical advantages over the PIN methodology. In addition, unlike PIN, VPIN allows for capturing asymmetric information risk variations at the intraday level since its calculation is updated in trading buckets throughout the day (Abad & Yagüe, 2012).

The major change from VPIN to PIN was based on Lei e Wu (2005) and Easley et al. (2008). Lei e Wu (2005) investigated the interactions between informed and uninformed traders in 40 stocks on The New York Stock Exchange (NYSE) and pointed out that the arrival flow of buy and sell orders is different and varies over time. According to them, the probability of informed trading associated with time, added by VPIN, would be a superior measure of information asymmetry than other existing ones. In turn, Easley et al. (2008) studied how trading dynamics interacted with order flow and the evolution of market liquidity and proposed a dynamic market microstructure model, which showed that both informed and uninformed trades are highly persistent. The authors calculated the estimation to generate daily rates of conditional orders of informed and uninformed trades, which were used to calculate PIN and predict market liquidity as indicated by the bid-ask spread. For the authors, the liquidity factor may be relevant for pricing assets, as there is a new generation of pricing models that incorporate the effect of market liquidity as a systematic risk factor. Similarly, other empirical evidence, such as Easley et al. (2002) and O'Hara (2003), differ on the liquidity measures employed but agree on their importance for asset pricing.

After that, based on intraday transaction data and aiming to achieve more effective risk measurements at the intraday level, Easley et al. (2011) formally introduced VPIN as an extension of the PIN model. They demonstrated how VPIN successfully signaled the Flash Crash of 2010, which peaked hours before the event occurred. This incident was characterized by a rapid crash of major US stock indices on May 6, 2010, including the S&P 500, Dow Jones, and Nasdaq, which plunged and partially recovered in less than an hour. The day was marked by high volatility in trading various assets such as equities, futures, and options contracts. Although these market indices partially recovered on the same day, the Flash Crash led to losses of nearly $1 trillion in the market value of companies traded on U.S. Exchanges (Pontuschka & Perlin, 2015).

Later, Easley et al. (2012) introduced the concept of a toxic market to represent the risk of adverse selection by market makers in the context of High-Frequency Trading (HFT); that is, the risk that market makers are trading with informed traders. To calculate the probability of information-based trading, Easley et al. (2012) represented order imbalances using a monotone function of the absolute price changes, supported by the trading intensity and volume imbalance, which resulted in VPIN. This measure was then used to predict toxicity-induced market volatility. The central idea is that market makers face the prospect of losses due to adverse selection when order flows become unbalanced, and this toxicity estimate varies over time. Suppose market makers believe that market toxicity is high. In that case, they will liquidate their positions and leave the market, which, in turn, will impact liquidity.

In addition to being updated in time and calibrated to have an equal volume of transactions in each time interval, the VPIN approach does not require the estimation of unobservable parameters and, in this sense, overcomes the obstacles of PIN in HFT markets (Easley et al. 2012). VPIN can be calculated by Equation 1 below.

$$VPIN = \frac{\alpha\mu}{\alpha\mu + 2\varepsilon} = \frac{\alpha\mu}{V} \approx \frac{\sum_{\tau=1}^{n} |V_\tau^S - V_\tau^B|}{nV} \tag{1}$$

Where V_τ^S is the volume of sell orders from each bucket (trading lot consisting of one-fiftieth of the daily trading volume); V_τ^B is the volume of buy orders from each bucket; *V* is the volume of each bucket, and *n* is the number of buckets used to approximate the expected imbalance.

Empirical evidence on VPIN efficiency has proven to be diverse. On the one hand, Easley et al. (2011) and Bethel, Leinweber, Rübel and Wu (2012) showed that VPIN could have predicted the 2010 Flash Crash. Also, in studying the estimation process of VPIN using a sample of 15 stocks from the Spanish market, Abad and Yagüe (2012) concluded that the model is a straightforward way to measure adverse selection risk, and it fits the HFT market adequately. Similarly, Yildiz, Ness, and Ness (2020) found evidence that variations in VPIN provide (i) information about changes in U.S. stock market liquidity and (ii) revenues for liquidity providers and losses for liquidity demanders through adverse selection on an ex-ante basis. According to these authors, these results support the view that VPIN can be an ex-ante warning signal for deteriorating stock market liquidity. In addition to liquidity, Yildiz et al. (2020) argue that VPIN can also be an effective predictor of market volatility. Indeed, the authors found that changes in VPIN are positively related to the expected volatility of stock returns. Thus, they concluded that tracking VPIN can be beneficial for market makers, regulators, and traders by providing them with information about future market liquidity and ex-ante return volatility in North American stock markets.

On the other hand, the efficiency of VPIN as a predictor of liquidity crises induced by toxicity and price volatility has been questioned by some researchers, including Andersen and Bondarenko (2014) and Abad, Massot and Pascual (2018). For example, Andersen and Bondarenko (2014) have found no evidence of the incremental predictive power of VPIN for future volatility. Moreover, they argued that VPIN properties depend heavily on the classification of the underlying transactions by the algorithm and that when employing other standard classification techniques, VPIN behaves opposite to that documented by Easley et al. (2011, 2012). Furthermore, these authors present empirical evidence supporting the hypothesis that VPIN is largely driven and significantly distorted by volume and volatility innovations.

Abad et al. (2018) calculated VPIN using intraday data for 45 stocks comprised by IBEX 35 – the main benchmark index of the Spanish stock market – from 2002 to 2013. They concluded that VPIN rarely indicates an abnormal lack of liquidity and occasionally anticipates large intraday price changes. Furthermore, they found significant differences in the incidence of liquidity and price between toxic and non-toxic periods identified by VPIN. Therefore, these authors' findings suggest that VPIN's ability to anticipate truly toxic events is limited.

2.3 Relationship between Market Liquidity and Order Flow Toxicity

Due to its potential to cause losses to uninformed traders, informational asymmetry leads such agents to liquidate their positions if they realize that they are trading with informed traders, reducing market liquidity. Therefore, studies such as Easley et al. (2011), Abad e Yagüe (2012), Chen, Chien e Chang (2012), and Agudelo, Giraldo e Villarraga (2015) have sought to understand the relationship between informational asymmetry and market liquidity.

Easley et al. (2011) argue that order flow toxicity in high-frequency markets can lead market makers to leave the market, thus causing illiquidity events. Abad and Yagüe (2012) corroborated this argument by pointing out that toxicity emphasizes a market maker's expected loss from being in the same environment as an informed trader; that is, the likelihood of market makers being targets of adverse selection.

For Agudelo et al. (2015), market microstructure models imply that informed trading reduces liquidity and moves prices in the direction of information. These authors used the dynamic PIN model of Easley et al. (2008) to test this implication in the six largest Latin American stock markets: Argentina, Brazil, Chile, Colombia, Mexico, and Peru. The dynamic PIN model of Easley et al. (2008) considers that order rates are time-varying and predictable and that both informed and uninformed orders are not constant over time; instead, they operate according to an autoregressive and correlated dynamic. The results of Agudelo et al. (2015) suggest that PIN dynamics are related to asset returns in addition to the effects on liquidity. Indeed, these findings contribute to the discussion on the accuracy of PIN as a metric of informed trading and a better understanding of price formation in emerging markets.

In studying the foreign exchange market, Chen et al. (2012) argued that the usual order flow model must be reformulated in broader terms to incorporate the transaction costs associated with the lack of liquidity. Using a daily order flow dataset, these authors measured liquidity in the foreign exchange market and concluded that order flows influence exchange rate returns for currencies with high trading density. However, they are inadequate when explaining changes in low-volume currencies. Moreover, according to these authors, both order flows and spreads significantly affect exchange rate returns for currencies with high trading volumes.

Regarding the relationship between informational asymmetry and liquidity, Siqueira et al. (2017) adopted the argument that the supply of liquidity by market makers is a complex phenomenon since traders may possess information about an asset that is not available to the first group. In high-frequency markets, market makers seek small gains that expand through transactions with large amounts of orders, and their gains depend exclusively on controlling the risk of being the target of adverse selection. The probability of gains for these market makers when trading large quantities of assets increases when there is a balance between order flows. In the absence of such balance, market makers can be targets of adverse selection. As a result, they will liquidate their positions due to the high toxicity, decreasing market liquidity (Siqueira et al., 2017).

Easley et al. (2011) examined the toxicity-liquidity relationship when studying the 2010 Flash Crash and suggested that this event was caused by a liquidity crisis, primarily due to the structural characteristics of the HFT market. These authors empirically tested the VPIN model in S&P 500 E-mini futures contracts from January 2008 to October 2010, highlighting the days close to the date of the Flash Crash. The results showed that VPIN predicted liquidity problems a few hours before the Dow Jones Industrial Average fell, reaching its highest value in the analyzed period minutes before the index crashed.

By analyzing only the exact date of the Flash Crash, Easley et al. (2011) found that VPIN peaked at the time of the index crash, remained high until the end of the day, and decreased as the index returned to the initial, pre-crash level. For these authors, trading in HFT markets is managed by algorithms that issue buy and sell orders, and therefore HFT firms are the major liquidity providers in these markets. As the order flow toxicity increases, these market makers, realizing that they are facing potential losses, reduce or liquidate their positions, leading to a decline in liquidity and serious repercussions for the traders involved, as happened in the Flash Crash.

Seeking to explain the toxicity-liquidity relationship in more detail, Easley et al. (2012) estimated VPIN for E-mini S&P 500 futures contracts traded from January 1, 2008, to August 15, 2011, using intraday data with one-minute intervals. They found that VPIN has significant predictive power over toxicity-induced volatility, making it a risk management tool for HFT markets.

Yildiz et al. (2020) also studied the toxicity-liquidity relationship through a sample of stocks that comprised the S&P 500 index in 2015. To do so, they used VPIN as a proxy for toxicity and the spread of market liquidity. As a result, these authors found that VPIN provides information about market liquidity and stock return volatility; and predicts adverse selection problems, thus indicating that VPIN can be a useful risk management tool for market makers in U.S. equity markets.

Martins and Paulo (2016) found a positive relationship between PIN and risk, cost of equity capital, liquidity, abnormal return, volatility, and firm size in the Brazilian stock market. In addition, they found a negative association between PIN and B3 corporate governance levels and American Depository Recipes (ADR) issuance. On the other hand, the unexpected results were related to market liquidity and firm size. According to these authors, it was expected that more liquid and larger firms – which are less exposed to information risk – would show an inverse relationship with these variables. However, due to the characteristics of the Brazilian market, which has a higher rate of preferred stock issuance – typically more liquid and belonging to larger companies – the authors observed positive relations between these proxies with PIN.

In the Brazilian derivatives market, Ribeiro et al. (2020), who studied the effect of informational asymmetry risk on the liquidity of agricultural commodity futures traded on B3, revealed a weak correlation between informational asymmetry (VPIN) and market liquidity (bid-ask spread). In addition, their findings revealed a positive relationship between informational asymmetry and market liquidity, diverging from what had been observed by Martins and Paulo (2016).

Given all this, there is ample room for discussion about the efficiency of VPINs in measuring order flow toxicity and, consequently, for analyzing the impact of this measure on other variables, such as market liquidity, which justifies conducting research aimed at testing their efficiency.

3 METHODOLOGY

3.1 Data and Sample

The population of this study consisted of buy and sell order flows of One-day Interbank Deposit Futures (DIs) and U.S. Dollar Futures. The sample consisted of intraday data on the trades of these orders from September 1, 2018, to August 31, 2019. This period was chosen due to the availability of data on B3's Market Data platform, used for data collection since B3 limited the amount of data available on its website, excluding older ones as it published the more recent ones. The data were treated, and the variables were calculated through Python Programming. The econometric model and the diagnostic tests were estimated using STATA software.

3.2 Analyzed Variables

The bid-ask spread (the dependent variable in the model) was used as a proxy for market liquidity and is represented by Equation 2.

$$Spread_\tau = ask_\tau - bid_\tau \tag{2}$$

Where $Spread_{\tau}$ is the difference between the lowest bid and the highest ask price within each trading bucket τ; ask_{τ} is the lowest bid price within each trading bucket τ; and bid_{τ} is the highest ask price within the bucket τ. In this sense, the larger the spread between the bid and ask price of a given security, the lower its liquidity. The bid-ask spread was calculated using Python Programming based on data available in B3's *Market Data* files. In these files, the aggressor order is highlighted in buy or sell. The choice of the bid-ask spread as a proxy for liquidity was inspired by Easley et al. (2008), Akay et al. (2012), Easley et al. (2012), Siqueira et al. (2017), among others.

The independent variable VPIN by Easley et al. (2012) was used as a proxy for toxicity and is represented by Equation 3. According to these authors, the speed at which VPIN updates is expected to simulate the speed of information arrival to the market.

$$VPIN = \frac{\sum_{\tau=1}^{n} |V_{\tau}^{S} - V_{\tau}^{B}|}{nV} \tag{3}$$

Where: V_{τ}^{S} is the volume of sell orders from each bucket; V_{τ}^{B} is the volume of buy orders from each bucket; *V* is the volume of each bucket, and *n* is the number of buckets used to approximate the expected imbalance. The estimation of VPIN depends on the determination of variables *V* and *n*. To calculate one-day VPIN, *V* equals one-fiftieth of the daily (bucket) trading volume, and *n* equals 50. Therefore, to calculate weekly VPIN, for example, the variable *n* would equal 250.

As shown in equation 3, to measure VPIN, the correct classification of transactions must be identified. However, identifying the aggressor side of the order available in B3's *Market Data* does not require a classification algorithm. Therefore, unlike Easley et al. (2012), who opted for the tick-rule (T.R.), this work adopted the actual classification provided by B3.

As control variables, the variables trading volume (*Vol*), number of trades (*TRA*), and price volatility (*VLA*) were used.

All variables, including the bid-ask spread, were calculated per trading bucket, the same ones used to obtain VPIN, ensuring that the number of observations was the same for all variables. Trading volume and number of trades are also available from B3's *Market Data*. Volatility was calculated by the difference between the highest and lowest prices, divided by the average prices, a procedure previously used by Yoon et al. (2011). Table 1 shows the dependent, independent, and control variables, as well as their definitions/calculation formulas and the theoretical and empirical foundations.

Table 1
Analyzed variables

Variables	Definition/Calculation	Theoretical Framework
$Spread$	$ask_{\tau} - bid_{\tau}$	Demsetz (1968); Easley et al. (2008); Agudelo et al (2015); Siqueira et al. (2017); Yildiz et al. (2020).
$VPIN$	$\frac{\sum_{\tau=1}^{n} \|V_{\tau}^{S} - V_{\tau}^{B}\|}{nV}$	Easley et al. (2008); Akay et al. (2012); Easley et al. (2012); Siqueira et al. (2017); Yildiz et al. (2020).

VOL	Traded Volume	Ding (1999); Yoon et al. (2011); Ribeiro et al. (2020).
TRA	Number of Trades	
VLA	Volatility	

Source: Prepared by the authors.

3.3 Estimated Model

Multiple Linear Regression (MLR) was employed to analyze the impact of VPIN on market liquidity, estimated through Ordinary Least Squares (OLS) regression. In addition, a model was estimated separately for each type of futures contract (DI and U.S. Dollar) and is represented by Equation 4.

$$|Spread|_i = \beta_0 + \beta_1 VPIN_i + \beta_2 TRA_i + \beta_3 VOL_i + \beta_4 VLA_i + e_i \quad (4)$$

Where β_0 is the intercept parameter; β_1, β_2, β_3 and β_4 are the coefficients associated with each of the model's explanatory variables; and e_i is the random error. The reason for choosing the absolute value of the bid-ask spread is the requirement to measure the distance of the result from zero to obtain the illiquidity proxy.

For the correct estimation of models, diagnostic tests must be performed to check whether the model meets the assumptions underlying it (Wooldridge, 2010). In this sense, tests were performed to check the normality, homoscedasticity, autocorrelation, and multicollinearity assumptions.

An important step when estimating an MLR model with time series data is to check whether the data follow a stochastic process, i.e., that the variables are random and not subject to temporal influence. Disregarding the possible temporal trend that a data series may contain compromises the model estimation, leading to erroneous conclusions that the change in the dependent variable is caused by the change in the independent variable when in fact, the cause is the temporal trend itself. Thus, checking whether the series is stationary or not is paramount. Stationarity is verified through unit root tests. When a given series has a unit root, it shows a trend over time and is thus classified as nonstationary, requiring model corrections. In this sense, two unit root tests in the literature were used: (i) the Augmented Dickey-Fuller (ADF) test; and (ii) the Phillips-Perron (PP) test. Suppose the results indicated by these tests are not unanimous. In that case, a third test can be performed (Kwiatkowski, Phillips, Schmidt e Shin – KPSS).

4 ANALYSIS AND DISCUSSION OF RESULTS

4.1 Descriptive Statistics

Table 2 presents the descriptive statistics of the bid-ask spreads (illiquidity) of DI and U.S. Dollar Futures. For DI Future, the mean was 0.02, the standard deviation was 0.88, the minimum value was -6.09, and the maximum value was 6.35. As expected, these values show high liquidity in the DI Futures market. The coefficient of variation was 44.0%, showing that the sample's bid-ask spread values have a stable dispersion around the arithmetic mean. For the U.S. Dollar Futures, the mean was 0.12, the standard deviation was 8.73, the minimum value was -86.50, and the maximum was 142. These values reveal high liquidity in the U.S. Dollar Futures market. However, it is less liquid than the DI Futures market. This result was expected since DI Futures are B3's most traded derivatives. The coefficient of variation was 72.75%, showing that the sample's bid-ask spread values have greater dispersion around the mean than the values found for DI Future.

These results (DI Future and U.S. Dollar Future) are lower than the values documented by studies that employed the bid-ask spread to measure the illiquidity of futures contracts traded by B3. Marquezin (2013) examined the cost of liquidity of soybean contracts traded on B3 from September 2010 to February 2013 and found an average bid-ask spread of 2.2. In turn, Tonin, Costa Junior and Martines Filho (2017), who estimated the liquidity cost of corn futures contracts traded on B3 between September 2015 and August 2016 using the bid-ask spread, found an average of 0.1599. As expected, the results show that the DI and U.S. Dollar Futures markets are more liquid than the soybean and corn futures. This happens because these commodities are less traded compared to the first ones.

Table 2
Descriptive statistics of the bid-ask spreads of DI and U.S. Dollar Futures

Type of Contract	Minimum	Maximum	Mean	Standard Deviation	CV
DI Futures	-6,09	6,35	0,02	0,88	44,0%
U.S. Dollar Futures	-86,50	142,00	0,12	8,73	72,75%

Source: Prepared by the authors.

VPIN by Easley et al. (2012) was used as a proxy for order flow toxicity for DI and U.S. Dollar Futures traded on B3. Fifty daily buckets were used to calculate VPIN, accounting for one-fiftieth of the daily traded volume, i.e., on each trading day, the daily trading volume was divided by fifty, resulting in 12,150 observations. Table 3 presents the descriptive statistics of VPIN for the negotiations of DI and U.S. Dollar Futures markets. For DI Futures, a 0.42 mean was found, along with a 0.31 standard deviation, a minimum of 0, and a maximum of 1. The coefficient of variation was 73.81%, showing that the sample's VPIN values have a high dispersion around the arithmetic mean. For the S&P500 E-mini index, covering the period from January 2008 to October 2010, Easley et al. (2011) found VPIN below 0.44 in 80% of the buckets; that is, slightly lower values if compared to those found in this research for the DI Futures trades. As for U.S Dollar Futures, the average VPIN value was 0.24, the standard deviation was 0.22, and minimum and maximum values were 0 and 1, respectively. The coefficient of variation was 91.67%, showing that the values of VPIN of the sample have a high dispersion around the arithmetic mean.

Table 3
Descriptive statistics of VPIN for DI and U.S. Dollar Futures

Type of Contract	Minimum	Maximum	Mean	Standard Deviation	CV
DI Futures	0	1	0,42	0,31	73,81%
U.S. Dollar Futures	0	1	0,24	0,22	91,67%

Source: Prepared by the authors.

The VPIN results for trading in U.S. Dollar Futures contracts reported here are slightly higher than those observed by Easley et al. (2012). These authors used data from S&P500 E-mini index futures contracts from January 1, 2008, to August 15, 2011, and found an average VPIN of 0.2251. When comparing these values, there is evidence that the risk of informational asymmetry in the Brazilian DI and U.S. Dollar Futures markets is similar to that of the U.S. futures market.

Indeed, Barbosa (2014) also examined the toxicity of the B3 DI and U.S. Dollar Future contracts from October 2010 to October 2011. VPIN was calculated using the bulk volume classification (BVC) and the tick-rule algorithms. The average values of DI Futures were 0.2686 and 0.2144, respectively. The average values of the U.S. Dollar Futures calculated using BVC and T.R. were 0.2451 and 0.3127, respectively. Therefore, the values found by Barbosa (2014) differ from those found in this work. However, this study did not adhere strictly to the procedure proposed by Easley et al. (2021) since the author did not rely on the daily volume traded but a moving average of ten trading days instead. Furthermore, the fact that VPIN values differ according to the classification algorithm used in this study is noteworthy. Therefore, it is worth pointing out the criticism of Andersen and Bondarenko (2014) in arguing that the effectiveness of VPIN is conditioned to the performance of the order classification algorithms.

4.2 Diagnostic and Unit Root Tests Results

Before presenting the results of the estimated models, this subsection presents the statistics of the diagnostic and unit root tests. The hypotheses underlying the classical multiple linear regression model must be tested to make inferences about the estimated coefficients. In this sense, Table 4 presents the statistics and p-values of the normality, homoscedasticity, autocorrelation, and multicollinearity tests.

The Jarque-Bera test was used to test normality, with a normal variable distribution as the null hypothesis. Based on the values of the test statistics (17,660.8 and 9,664.69 for the DI and U.S. Dollar Futures markets, respectively), which were statistically significant (p-value = 0), the null hypothesis was rejected, suggesting that the variable does not follow a normal distribution. Despite the significance of the normality test, Wooldridge (2010) emphasizes that if the sample size is large enough, according to the central limit theorem, the residuals tend to follow a normal distribution. Thus, the estimation of the models was not invalidated.

To check whether the residuals of the tested models are homoscedastic, we performed the Breusch-Pagan test, which tests the null hypothesis of the homoscedastic variance of the regression residuals. The p-values for the DI and U.S. Dollar Futures models were zero, i.e., the test revealed that heteroscedasticity is present in both models.

To identify autocorrelation, we performed the Breusch-Godfrey test, which has the absence of autocorrelation in the models as a null hypothesis. Based on the p-values obtained (zero for both models), the null hypothesis was rejected, showing that both models (DI and U.S. Dollar Futures) presented autocorrelation problems.

Finally, the values of the variance inflation factor (VIF) for the explanatory variables of the study were presented. According to Greene (2002), although this is an arbitrary choice, it is assumed that VIF values above 20 indicate collinearity problems. Hence, there is no evidence of collinearity problems among the variables analyzed.

Once the problems of heteroscedasticity and autocorrelation were identified in the data, challenging the regression model's assumptions, the correction of Newey e West (1987) had to be used. This allows the standard errors of the coefficients of the econometric model to be corrected for both heteroscedasticity and autocorrelation (Gujarati & Porter, 2011).

Table 4
Testing the linear regression model hypotheses

Test		**DI Futures**	**U.S. Dollar Futures**
Jarque-Bera	Chi-square	17660,8	9.664,69
	p-value	0,0	0,0
Breusch-Pagan	LM	20686,1	28.706,3
	p-value	0,0	0,0
Breusch-Godfrey	LM	1473,37	10,1215
	p-value	0,0	0,0
VIF	VPIN	1,10	1,01
	TRA	13,87	8,36
	VOL	13,98	8,50
	VLA	1,03	1,01

Source: Prepared by the authors.

Another important aspect of the proper estimation of the models was the application of unit root tests. When a series has a unit root, it is classified as nonstationary, which requires the transformation of the variables to make it stationary. Accordingly, the first step was performing ADF and PP tests. These have the presence of a unit root as a null hypothesis and differ in how the serial correlation is controlled when checking for a unit root. The ADF test incorporates, in a linear fashion, the lagged differences of the variable itself into the test equation, whereas the PP test relies on a non-linear method (Gujarati & Porter, 2011).

Table 5 presents the p-values of the ADF and PP tests for the DI and U.S. Dollar Futures bid-ask spread series. From the p-values presented in this table, the null hypothesis of the presence of a unit root was rejected; that is, the bid-ask spread series of the DI and U.S. Dollar Futures are stationary.

Table 5
Unit root test

Teste		**DI Futures**	**U.S. Dollar Futures**
ADF	*p-value*	0,0	0,0
PP	*p-value*	0,0	0,0

Source: Prepared by the authors.

Therefore, the parameters of the estimated models were obtained by the OLS method. The next section discusses the estimation results of the models built for DI and U.S. Dollar Futures.

4.3 Relationship between Order Flow Toxicity and Market Liquidity

Table 6 presents the estimated coefficients for the DI Futures model and their respective significance level. Indeed, VPIN was positive and statistically significant. It can be observed that for a one-unit variation in VPIN, the variation in the bid-ask spread is 0.10. The control variables' parameters also proved to be statistically significant (p-value = 0.0). As for the model's coefficient of determination, the independent variables considered can explain about 44% of the total variation in the bid-ask spread. This result indicates that, in addition to the variables analyzed, other factors influence the bid-ask spread in the DI Futures market.

Table 6
Econometric model estimates for DI Futures trades

|Spread|	**Coef.**	**Std. Err.**	**t**	**P>|t|**
Constant	0,16	0,01	10,76	0,0
VPIN	0,10	0,02	5,34	0,0
TRA	-0,000002	0,000001	-15,95	0,0
VOL	0,000003	0,0000002	15,29	0,0
VLA	1,08	0,05	20,11	0,0
Prob > F = 0,0			R-Squared = 0,44	

Source: Prepared by the authors.

The results of the estimated model for the U.S. Dollar Futures are shown in Table 7. VPIN was positive and statistically significant. For a one-unit variation in VPIN, the variation in the bid-ask spread is 0.76. Thus, the informational asymmetry risk in the U.S. Dollar Futures market has a greater influence on the bid-ask spread than in the DI Futures market. All parameters of the control variables of this model were statistically significant. The coefficient of determination shows that the model's percent of variance explained is 35% (R-squared=0.35), i.e., smaller than the DI Futures model.

As in the DI Futures model, the coefficient for volume and volatility in the U.S. Dollar Futures model showed a positive relationship with the bid-ask spread, whereas the coefficient for trades was negative. This result is consistent with the literature, particularly in Ding (1999) and Yoon et al. (2011). In both models, DI Futures and U.S. Dollar Futures, the relationship between VPIN and the bid-ask-spread is positive, which is in line with previous studies and shows that the risk of informational asymmetry reduces market liquidity in the trading of these contracts.

Table 7
Econometric model estimates for U.S. Dollar Futures trades

|Spread|	**Coef.**	**Std. Err.**	**t**	**P>|t|**
Constant	1,41	0,39	3,23	0,0
VPIN	0,76	0,24	3,17	0,0
TRA	-0,0004	0,0003	3,15	0,05

VOL	0,0000002	6,21e-08	10,99	0,0
VLA	0,07	0,006	3,66	0,0
Prob > F = 0,0			R-Squared = 0,35	

Source: Prepared by the authors.

After presenting the results, we seek to collate them with theory and empirical evidence of the relationship between order flow toxicity and market liquidity. Indeed, Bethel et al. (2012) argued that VPIN would have been efficient in predicting evidence of the Flash Crash, a result corroborated by Easley et al. (2011, 2012).

In the Brazilian stock market, Siqueira et al. (2017) found a high level of toxicity in stock order flows. By adding VPIN to the three- and five-factor models of Fama and French (1993, 2015) and the four-factor model of Carhart (1997), these authors showed that informational asymmetry is priced in the Brazilian stock market. In the U.S. market, Yildiz et al. (2020) analyzed the toxicity-liquidity relationship in the stocks in the S&P500 index and found that VPIN negatively impacts market liquidity and can indicate adverse selection problems.

Agudelo et al. (2015), who tested the hypothesis of a positive relationship between informational asymmetry (dynamic PIN) and illiquidity (bid-ask spread) in Latin American markets – including Brazil – found evidence that informed trading causes prices to move in the direction of information and simultaneously reduces liquidity, as predicted by the literature on market microstructure.

On the one hand, the results of this paper do not corroborate the direction of the relationships between liquidity and informational asymmetry documented by the authors mentioned above. Although the models estimated for DI and U.S. Dollar futures trades have different explanatory power (44% and 35%, respectively), both were highly significant and endowed with higher explanatory power than that documented by Ding (1999) and Yildiz et al. (2020), who found coefficients of determination of 32.96% and 19.55%, respectively. Unlike Agudelo et al. (2015) and Yildiz et al. (2020), in the two models estimated in the present analysis for DI and U.S. Dollar Futures, the relationship between informational asymmetry (VPIN) and illiquidity (bid-ask spread) was positive. In other words, an inverse relationship was found between informational asymmetry and liquidity for these markets, corroborating the findings by Martins and Paulo (2016) for the stock market.

On the other hand, the results discussed here differ from those observed in other studies, such as Ribeiro et al. (2020), who analyzed the agricultural commodity futures market. These authors found a direct relationship between informational asymmetry and market illiquidity. However, the correlation between VPIN and bid-ask spread observed by Ribeiro et al. (2020) proved to be weak (0.02), well below the value of 0.4 found by Easley et al. (2012).

Studies such as Abad et al. (2018) have pointed out the limitations of VPIN in signaling order flow toxicity and tested whether VPIN is an efficient indicator of liquidity crises induced by toxicity and price volatility. They concluded that VPIN rarely indicates abnormal liquidity shortages. Therefore, according to these authors, VPIN's ability to anticipate truly toxic events is limited.

In this analysis, the models associating VPIN with the bid-ask spread showed moderate explanatory power, in addition to showing that the VPIN values found for the analyzed futures contracts are similar to those recorded in other studies, such as Easley et al. (2011, 2012) and Siqueira et al. (2017). Thus, it was documented in this work that VPIN is one of the factors that impact liquidity in the DI and U.S. Dollar Futures markets.

5 CONCLUSION

This study provides empirical evidence that informational asymmetry is crucial in determining the liquidity of securities traded in the Brazilian capital market. Therefore, it reveals that aspects associated with the microstructure of markets can contribute to the pricing of assets traded in this market. More specifically, this article aimed to analyze the impact of order flows toxicity for DI and U.S. Dollar Futures contracts traded at B3 on the market liquidity of these assets.

To analyze this relationship, the first step of this empirical study consisted in calculating the flow toxicity of buy and sell orders for DI and U.S. Dollar Futures contracts traded on B3 from September 1, 2018, to August 31, 2019. VPIN by Easley et al. (2012) was the metric chosen to measure the toxicity of order flow in these markets. The other variables used were collected directly from B3's Market Data file. In the second step, diagnostic tests of the linear regression models' hypotheses were conducted, as well as unit root tests, which revealed the need to use estimators with correction for data heteroscedasticity and autocorrelation. Finally, the regressions of the bid-ask spread on VPIN for DI and U.S. Dollar Futures were estimated separately. Besides VPIN, as in Ding (1999) and Yoon et al. (2011), the control variables volume, trades, and volatility were included in the specifications.

Initially, the analysis consisted in presenting the descriptive statistics of the bid-ask spread (market illiquidity proxy) and VPIN (order flow toxicity proxy). As expected, these statistics revealed the high liquidity of the DI and U.S. Dollar Futures markets. Furthermore, the DI Futures contracts proved to be more liquid than the U.S. Dollar Futures contracts. Similarly, the summary statistics for VPIN were similar to the values found by other studies on toxicity for both the DI and the U.S Dollar Futures markets.

Subsequently, the estimated relationship between VPIN and the bid-ask spread proved positive and statistically significant for DI and U.S. Dollar Futures. Therefore, the results suggest that information asymmetry is one of the factors impacting the market liquidity of B3 assets analyzed here, although the direction of the association was contrary to expectations. This result leads one to reflect on the meaning of the liquidity and asymmetry metrics used. For example, one could conjecture that the bid-ask spread reflects the risk of the assets. In this case, the relationship found here would be consistent with market microstructure models. Alternatively, as Duarte and Young (2009) question, perhaps PIN is priced in because of order imbalances or other liquidity effects unrelated to information asymmetry.

Based on the results found here, the imbalance of buy and sell orders can signal liquidity crises in the analyzed futures markets and, consequently, indicate that tracking VPIN is a relevant factor for investment decisions of financial market actors and market regulators. For example, VPIN can assist regulators and market participants in understanding price volatility. Therefore, the frequent use of liquidity crisis signaling measures such as VPIN can contribute to the stability of financial markets.

This study contributes particularly by identifying the relationship between informational asymmetry and market liquidity, which needs to be investigated more closely since it is one of the factors impacting asset returns. However, this study has the limitation of restricting the analysis to a sample of only two types of contracts traded on the futures market. Moreover, considering that the explanatory power of the models estimated here was not high for any of the assets, other factors such as cyclical aspects (macroeconomic) or microstructure characteristics of the markets analyzed are determinants of market liquidity as well. Therefore, we suggest that future research considers other derivative products to analyze the informational asymmetry-liquidity relationship, such as futures contracts based on the Ibovespa Index, in addition to identifying macroeconomic or market microstructure aspects that may improve the explanatory power of the models.

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AUTHORS' CONTRIBUTIONS

Contributions	João Eduardo Ribeiro	Laise Ferraz Correia	Felipe Dias Paiva
1. Idealization and conception of the research subject and theme	✓	✓	
2. Definition of the research problem	✓	✓	
3. Development of Theoretical Platform	✓	✓	✓
4. Design of the research methodological approach	✓	✓	✓
5. Data collection	✓		
6. Analyses and interpretations of collected data	✓	✓	✓
7. Research conclusions	✓	✓	✓
8. Critical review of the manuscript	✓	✓	
9. Final writing of the manuscript, according to the rules established by the Journal.	✓		
10. Research supervision	✓	✓	✓