The probability of informed trading and stock liquidity

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ABSTRACT

This study examines the effect of the probability of informed trading on the stock liquidity. The methodology relies on linear regressions using the method of ordinary least square is used for a sample of manufacturing companies listed on the Tehran Stock Exchange in the period 2012-2016. We use five measures of stock liquidity that include Turnover Ratio, Amihud illiquidity, Bid-Ask spread, Free Floating ratio, Liquidity Index. As for information asymmetry between informed and uninformed traders, we utilize the variable Probability of informed trading (PIN). The results of the regression analysis indicate that Probability of informed trading has a positive and significant effect on the Turnover Ratio measure and Amihud illiquidity measure, but Probability of informed trading has no significant effect on the Bid-Ask spread measure, Free Floating ratio measure and Liquidity Index, suggesting that stocks with higher probabilities of information-based trading, PIN, have higher Turnover Ratio and Amihud illiquidity measure. These results highlight the informed trader’s role in defining the level of liquidity on the Tehran Stock Exchange. This paper provides novel evidence on the influence of Probability of informed trading (PIN) on stock liquidity in an emerging market context.

Keywords:

Information asymmetry, Probability of informed trading, Stock liquidity.

1. Introduction

Information asymmetry appears where one investor or several investors has/have confidential information about the value of an enterprise while most of investors have only the publicly available information (Brown & Hillegeist, 2007). As identified in literature, two of the effects of information asymmetry has been adverse selection which presents a situation where the type or quality of an asset is unknown by one party in a transaction; while moral hazard presents a situation where there is a hidden action that results from the transaction. Of particular concern in this study is the adverse-selection problem. Literature works on the concept of informed trading which refers to trading with private information. Specifically, an informed trader either obtains information before it is public or interprets publicly available information better than others do. There exist various measures of informed trading and information asymmetry in market microstructure literature. The probability of informed trade (PIN) is a popular measure of information asymmetry between informed and uninformed traders. The value of PIN is derived from the market microstructure model in Easley and O'Hara (1992). Since PIN cannot be measured directly, it must be estimated by numerical maximization of the likelihood function specified by the underlying microstructure model. The Probability of Informed Trade (PIN) model, developed in a series of seminal papers including, Easley and O'hara (1987), Easley, Kiefer, O'hara, and Paperman (1996), and Easley, Kiefer, and O'Hara (1997b), Easley, Kiefer, and O'Hara (1997a) has been used extensively in accounting, corporate finance and asset pricing literature as a measure of information asymmetry. The PIN model is based on the notion, originally developed by Glosten and Milgrom (1985), that periods of informed trade can be identified by abnormally large order flow imbalances.

The concept of Market liquidity is highly dependent on informational transparency. High liquidity allows companies to raise additional funds on favorable terms through low transaction costs and no time lag between economic agents (Glosten & Milgrom, 1985; Stoll, 1978). The presence of information asymmetry in the market may reduce liquidity (Jacoby, Fowler, & Gottesman, 2000). Several recent analytical papers have extended the analysis of the impact of information asymmetry on market liquidity to permit public disclosure of information (Diamond & Verrecchia, 1991; Kim & Verrecchia, 1994; McNichols & Trueman, 1994). These papers examine trading activity and market liquidity around well-defined information events. Easley and O'hara (1987) Provide a theoretical explanation for the impact of large trades in which an adverse selection trading problem occurs because informed traders are willing to trade larger amounts at any given price. Note that O'Hara (2003) argues that the cost of equity will be higher when there is more information asymmetry in capital markets and liquidity will be less among traded stocks. Glosten and Milgrom (1985) Show that the presence of traders with superior information leads to wider bid-ask spreads. Market makers are compensated for their anticipated losses to informed traders by widening the spread. In related literature, Copeland and Galai (1983) find that bid-ask spread increases with price volatility and the price level of the assets being traded, and decreases with trading volume. Diamond and Verrecchia (1991) Show in the form of a theoretical mode that a high-quality disclosure reduces information asymmetries between informed and uninformed investors. This reduction then increases the confidence of investors and increases the number of transactions of the Company's securities. In the end, market liquidity increases. Stoll (1978) Suggests that market makers' losses to informed traders are greater for stocks with greater turnover rates.

The Probability of Informed Trade (PIN) model, developed in a series of seminal papers including, Easley and O'hara (1987), Easley, Kiefer, O'hara, and Paperman (1996), and Easley, Kiefer, and O'Hara (1997b), Easley, Kiefer, and O'Hara (1997a) has been used extensively in accounting, corporate finance and asset pricing literature as a measure of information asymmetry. The PIN model is based on the notion, originally developed by Glosten and Milgrom (1985), that periods of informed trade can be identified by abnormally large order flow imbalances. Consistent with prior research, we measure Probability of informed trading the methodology of EHO model. Easley, Hvidkjaer, and O'hara (2002) Suggest a factorization of the PIN likelihood function to reduce computer over/under-flow. To measure Stock liquidity, we use Turnover Ratio, Amihud illiquidity; Bid-Ask spread, Free Floating ratio, Liquidity Index. We find that Probability of informed trading is positively associated with the Turnover Ratio and

Amihud illiquidity. These results are consistent with the information asymmetry between those who possess private information and uninformed agents (informed and uninformed investors) can have a negative impact on market liquidity, which confirms the adverse selection hypothesis. In empirical tests, Easley et al. (1996) find a strong positive relation between the probability of informed trades and spreads.

This paper aims at providing additional arguments about emergent markets, and more specifically, filling a gap of investigating probability of informed trades and stock liquidity in the context of Iran equity markets. Therefore, it is believed that this research will give a ground for a further investigation and interest in the probability of informed trades and stock liquidity in the Tehran stock exchanges. Moreover, this study makes several contributions to the literature. First, we add to the relatively new literature examining the Probability of informed trading by examining how it influences stock liquidity. Some of our findings are consistent with prior research. Second, this study contributes to the stock liquidity literature. From a practical point of view, it is expected that this paper will give another stimulus for Tehran stock exchanges policy makers to ensure the equal access to information for market participants. In addition, the paper presents empirical evidence of what drives stock liquidity in the Tehran stock markets which should be highly relevant for ordinary traders.

The remainder of the paper is organized as follows. Section two provides a review existing literature and develops a theoretical framework for our hypotheses. Section three describes the sample and the applied research methodology. Section four discusses the empirical results and Section five provides the conclusions.

2. Literature Review and Hypotheses Development

This paper is related and contributes to several areas of research: Information asymmetry between informed and uninformed traders theory, stock liquidity theory.

2.1. Literature on Information asymmetry between informed and uninformed traders

First, consider the difference between the information asymmetry risk faced by a dealer and the information asymmetry risk that concerns accounting regulators. The risk facing the dealer is not a measure of the long-run fundamental risk of investing in a particular firm. Rather, it reflects the short-run risk of trading with an informed trader. The dealer's concern is that an informed buyer (or seller) will be followed by a sequence of buys (or sells), driving the price up (down) and preventing him from unwinding his growing short (long) position. Therefore, a market maker's main concern is over the short horizon. He wants to know what the order-flow imbalance will be over the next 15 minutes, half hour, or trading day. While this liquidity risk is often referred to as information risk in the market microstructure literature, it can be distinguished from the risk investors face due to structural differences in the accounting information environment. Accounting regulators are primarily interested in long-term informational disparities between informed and uninformed traders caused by structural differences in access to information. While such structural differences in firms' disclosure policies are related to the likelihood of encountering an informed trader on a given day, other factors may be important in determining cross sectional spreads(C. M. Lee & Yahn, 1997) . Information asymmetry occurs when one party to an anticipated transaction has information that other doesn't have, in so doing passing on some benefits to that party (Akerlof, 1970). The challenges and opportunities created by information asymmetries are foundational elements of many theories, including agency theory (Jensen & Meckling, 1976), transaction cost economics (Williamson, 1975), resource-based theory (Barney, 1991), institutional theory (Powell & DiMaggio, 2012; Zucker, 1987), resource-dependence theory (Pfeffer & Salancik, 1978), and signaling theory (Spence, 1978). Management researchers have applied information asymmetry in a variety of ways. “Private information” often arises in explanations of competitive advantage and resource-based theory, “different information” is commonly construed in market-level efficiencies, “hidden information” is often associated with agency theory as it is depicted as leading to adverse selection and moral hazard, a “lack of perfect information” frequently leads parties to send and assess signals, and “information impactedness” is generally constructed as a source of transaction costs. Viewed broadly, the five categories of applications seem to coalesce into two distinct yet interrelated subgroups: (a) creating/sustaining advantage relative to forces for and against transparency and (b) creating hazards that parties seek to perpetuate or remedy through signals, screens, and ex ante and ex post actions (Bergh, Ketchen Jr, Orlandi, Heugens, & Boyd, 2019).

Information asymmetry appears where one investor or several investors has/have confidential information about the value of an enterprise while most of investors have only the publicly available information (Brown & Hillegeist, 2007). Literature works on the concept of informed trading which refers to trading with private information. Specifically, an informed trader either obtains information before it is public or interprets publicly available information better than others do. There exist various measures of informed trading and information asymmetry in market microstructure literature. The traditional asset-pricing models with symmetric information assume that prices are always fully revealing. In contrast, the microstructure models explicitly account for the process of price discovery. That is, the microstructure models study how private information is incorporated into prices through trading. Information asymmetry manifests itself when investors trade on the basis of their private information. While it is not possible to identify which trades are based on private information, the presence of privately informed traders in the market can be inferred from large imbalances between the number of buy orders and the number of sell orders. This operability provides the intuition behind the microstructure model developed by Easley et al. (1997a) and Easley et al. (1997b), called the EKOH model of information asymmetry. The EKOH model is a learning model in which the market maker draws inferences about the presence and the type of private information-based on the observed order flow. Over a trading day, prices converge to their full information levels as private information is fully revealed through the trading activities of informed investors. Thus, one can estimate the probability of information-based trades (PIN) for a given stock over a particular period based on the daily order flow during the period (He, Wang, & Wei, 2011). Simsir and Simsek (2018) show an abnormal trading volume around the first private notification times which is right before public disclosure announcements made public in BIST. They argue that the profits from the trades right before an announcement made public can sum up to 77 million $. Ojah, Muhanji, and Kodongo (2020) document that effective insider trading law improves stock price informativeness in South Africa.

2.2. Literature on stock liquidity

There is substantial literature on the liquidity of stocks. Balasemi, Veiseh, and Malgharani (2015) Describe liquidity as the buying and selling of a security with no considerable change in the price. Liquidity has proved to be difficult to observe, which has led to a number of liquidity measures being established in the academic literature including trading volume, bid-ask spread, zero-trading, zero-return days and various price impact models such as the Amihud ratio (Fong, Holden, & Trzcinka, 2017). A limited number of studies have linked liquidity to stock returns. Amihud, Mendelson, and Pedersen (2005) Believe that liquidity predicts future returns. In addition, Baker and Stein (2004) show a positive relationship between liquidity and stock returns. Liquidity generally means how easy it is to buy and sell a firm's securities. It contains the following three aspects of transaction costs in capital markets: tightness, resiliency, and depth. Tightness means the cost of turning around a position in a short period of time. Resiliency means the speed with which prices recover from a random, uninformative shock. Depth refers to the size of order flow imbalance required to change prices a given amount. Liquidity in this study should be interpreted as depth, since resiliency and tightness are not examined. See also Black (1971) for an extensive discussion of market liquidity. Why is liquidity important? The topic of liquidity has received substantial attention from both academics and popular press. Increase in liquidity can lead to improved sharing of financial risks by influencing investors' trading decisions due to reduction in transaction costs associated with making portfolio changes. Trading costs are large and economically significant (~1%) for large stocks in comparison to expected returns on stocks. Liquidity also plays a critical role in the price discovery process.

Stock market liquidity is an essential market characteristic whose presence ensures smooth functioning of the market, whereas its absence causes uneasiness in the market. Brennan, Chordia, Subrahmanyam, and Tong (2012) Refer to stock market liquidity as the ability of the market to absorb a huge volume of securities at a lower execution cost within a short period without having a significant effect on security prices. A liquid market is generally referred to as the market in which a large quantity is traded without any delay at lower transaction costs with minimum price impact. The previous literature proposes four main characteristics of liquidity that is, trading quantity, execution time, transaction cost, and price impact. Thus, the reviewed studies have measured liquidity in the stock market by using a variety of liquidity measures that can fairly capture the key market liquidity characteristics, that is, depth (volume or quantity measure), breadth (price impact measure), immediacy (time or speed measure), and transaction costs (spread or transaction cost measure). Moreover, these measures were computed either based on intraday (high-frequency) data or daily, weekly, monthly, quarterly, yearly (low-frequency) data. Although measures based on high-frequency data have been mainly in practice, Goyenko, Holden, and Trzcinka (2009) evidenced that the low frequency measures can be fairly used over high-frequency ones to measure liquidity. In addition, C. F. Lee and Lee (2015) suggested that measures based on low-frequency data enable in studying liquidity over a long period and across different market structures. Although, different measures of liquidity have been used and proposed in the literature, Chai, Faff, and Gharghori (2010) concluded that there is no best measure that can be used to measure the market liquidity because every type of measure captures different aspects of market liquidity in different market systems and conditions. Goyenko et al. (2009) Suggest that a researcher should choose a liquidity measure depending on the objective of his study. Researchers have shown a keen interest in analyzing the effect of different factors influencing liquidity of individual stocks and of the overall market, and have obtained significant results. Researchers have shown a keen interest in analyzing the effect of different factors influencing liquidity of individual stocks and of the overall market, and have obtained significant results. The studies have revealed a significant impact of regulatory policy announcements on liquidity. Besides, market volatility has been identified as a strong determinant of stock liquidity. Another determining factor evaluated is trading activity by different types of investors. The effects of stock exchange mergers and developments in the trading systems have been also analyzed as an influential factor of stock market liquidity. Studies have also evidenced that the corporate announcements and disclosures enhance transparency about the prospects of the firm and thus contribute to improving stock liquidity. The previous studies have also evaluated the relevance of corporate governance in determining stock market liquidity. In addition to the above, company-specific factors also have shown a significant effect on stock liquidity (Naik & Reddy, 2021). A number of other studies find a positive relation between expected return and illiquidity; see , Amihud et al. (2005) and Amihud, Mendelson, and Pedersen (2013).

2.3. Information asymmetry between informed and uninformed traders and stock liquidity

In their seminal work, Glosten and Milgrom (1985) laid out the properties of such an "adverse selection" component of the bid-ask spread in a market where trades arrive sequentially. Using a highly stylized model, they isolate the effect of the adverse selection problem the market maker faces. Assuming that the market maker is risk neutral and behaves competitively, they concluded the following: (1) the bid-ask spread increases as the informed-trader's information is more superior; (2) the bid-ask spread increases if the ratio of informed to noise trader's order arrival rates increases; (3) the transaction price reflects the market maker's update on the valuation of the asset given all the trades up to the current transaction; and (4) the price process converges to the valuation of the informed trader. In other words, the price revision is dependent on the probability of the market maker running into an order initiated by an informed trader, or the adverse selection risk. The price will eventually catch up to the value implied by the private information. These conclusions have immediate implications for market liquidity. The bid-ask spread is often referred to as the tightness of the market, which is one dimension of the market liquidity. Given the conclusions of Glosten and Milgrom (1985), an infinitely liquid market will have very small bid-ask spread. In fact, the liquidity of the market is driven by the adverse selection risk. The higher the probability that the market maker will run into informed trader, the larger the bid-ask spread and therefore the less liquid the market would be. The seminal work of Akerlof (1970) contends that information asymmetry can cause issues related to agency conflicts among corporate managers and investors that can diminish the volume of trades in capital markets. In other words, information asymmetry is key in understanding a firm’s stock market liquidity where in firms with poor disclosure and transparency should suffer from a lower level of stock market liquidity (Diamond & Verrecchia, 1991; Kurlat, 2018). Along this line, studies provide empirical evidence that higher stock market liquidity is associated with higher disclosure ratings, better transparency appraisals by analysts, and stricter disclosure requirements by the stock market (Leuz & Verrecchia, 2000; Welker, 1995). Another strand in the literature contends that there is significant information asymmetry among different categories of traders within the market. Due to having heterogeneous investment-related information, informed traders tend to outperform their uninformed counterparts, i.e., market makers, and other market participants (Grossman & Stiglitz, 1980; Kyle, 1985). When faced with changes in such information asymmetry, or in the likelihood of dealing with sophisticated informed traders, uninformed traders react by altering bid ask spreads (Easley & O'hara, 1987; Glosten & Harris, 1988). Healy and Palepu (2001) Thus conclude that the overall transparency and information environment of stocks is a significant determinant of stock market liquidity.

In empirical tests, Easley et al. (1996) find a strong positive relation between the probability of informed trades and spreads. Botosan and Frost (1998) Study the relationship between disclosure and stock market liquidity on a sample of firms listed on the NYSE. The authors find a negative but not significant relationship between the bid ask spread and corporate disclosure. Stoll (1978) Suggests that market makers’ losses to informed traders are greater for stocks with greater turnover rates. A number of studies find a positive relation between expected return and illiquidity; see Amihud et al. (2005) and Amihud et al. (2013), and Amihud, Hameed, Kang, and Zhang (2015).

Having studied this relationship, researchers rely on two main hypotheses. The first one is the trading hypothesis, according to which, the transaction volume induced by more transparency enhances stock liquidity. Indeed, rich informational environment attracts investors who will be encouraged to make transactions. This results in lower transaction costs, and hence, better market liquidity (Healy & Palepu, 2001). The second hypothesis is the adverse selection, assuming the existence of an informational asymmetry between informed and uniformed investors. Signaling through information’s mechanisms leads to decrease the adverse selection component of the spread, and hence, to increase market liquidity (Glosten & Milgrom, 1985). The study of the relationship between information disclosure and liquidity requires the existence of two types of costs (adverse selection costs and transaction costs). These costs may be mitigated by the mechanisms of corporate information (Ajina, Sougne, & Lakhal, 2015). The information asymmetry between those who possess private information and uninformed agents (informed and uninformed investors) can have a negative impact on market liquidity, which confirms the adverse selection hypothesis. On the other hand, the signal theory developments claim that such a share-ownership is a governance mechanism. It should by nature encourage investors to invest in these companies and therefore increase transaction volumes and market liquidity.

2.4. Hypothesis development

As we previously discussed in this section, probability of informed trading effect on the stock liquidity. Therefore, we pose the hypothesis of this study as follows:

Hypothesis One: There is a significant relationship between probability of informed trading and turnover measure.

Hypothesis Two: There is a significant relationship between probability of informed trading and Amihud's illiquidity measure.

Hypothesis Three: There is a significant relationship between probability of informed trading and Bid-Ask spread measure.

Hypothesis Four: There is a significant relationship between probability of informed trading and free floating measure.

Hypothesis Five: There is a significant relationship between probability of informed trading and stock liquidity Index measure.

3. Research Methodology

3.1. Sample construction

The initial sample consists of firm-year observations in the Tehran Stock Exchange database for the period 2012–2016. In order to draw a robust conclusion, we apply the following data filters: Firstly, we exclude financial firms as they have a capital structure, different from other firms. Secondly, we remove firm-year observations missing data in estimating variables. Thirdly, a firm must have at least 60 days of stock data in a fiscal year so that it is included in the sample in order to measuring pin, in which the sample size decreases by firm-years. As a result, our final sample consists of 565 firm-year observations that correspond to 113 firms. Financial data related to stock prices, trading volumes and bid and ask prices were retrieved from the Tehran stock exchanges database. Data related to number of days for which trading for stock were hand-gathered from annual reports. The accounting data were extracted from companies' annual reports.

3.2. Measurement of Variables

Dependent Variable - Stock Liquidity (LIQ)

Liquidity is generally described as the ability to trade large quantities quickly at low cost with little price impact. This description highlights four dimensions to liquidity, namely, trading quantity, trading speed, trading cost, and price impact. Researchers have examined the importance of liquidity in explaining the cross-section of asset returns, and empirical studies have employed several liquidity measures. Existing measures typically focus on one dimension of liquidity. For example, the bid-ask spread measure in Amihud and Mendelson (1986) relates to the trading cost dimension, the turnover measure of Datar, Naik, and Radcliffe (1998) captures the trading quantity dimension, and the measures in Amihud (2002) and Pástor and Stambaugh (2003) employ the concept of price impact to capture the price reaction to trading volume (Liu, 2006). Since the quoted spread, Amihud illiquidity measure, and turnover ratio are daily data, we use their means during each period in the empirical analysis.

Liquidity based on volume -Turnover Ratio (TOR)

This measure is an indicator of trading frequency and market depth and is a measure of liquidity (Datar et al., 1998; Lesmond, 2005). The higher is turnover means the higher stock liquidity. According to Easley and O'Hara (1992) and Engle and Russell (1998), liquidity proxy of a security is calculated using the equation below:

$$TOR_{it} = \frac{1}{D_{i,t}} \sum_{d=1}^{D_n} \frac{V_{i,d,t}}{N_{i,d,t}} \qquad (1)$$

Where D_{it} is the number of days for which trading for stock i in year t, and V_{idt} and N_{idt} are the number of shares traded and number of shares outstanding for stock i on day d in year t.

Liquidity based on price impact - Amihud illiquidity (ILLIQ)

The "illiquidity" measure proposed by Amihud (2002) is defined as the average ratio of the daily absolute return to trading volume on that day. The smaller is Amihud illiquidity, the higher is stock liquidity. Prior studies suggest that Amihud's (2002) measure is one of the best price impact proxies since it is seen to be highly correlated with other benchmark proxies that measure stock market liquidity (Fong et al., 2017; Goyenko et al., 2009; Marshall, Nguyen, & Visaltanachoti, 2012). Amihud's illiquidity measure for Stock i in year t is defined as follows.

$$ILLIQ_{it} = \left(\frac{1}{D_{i,t}} \sum_{d=1}^{D_{i,t}} \frac{|R_{i,d,t}|}{VD_{i,d,t}} \right) \times 10^6 \qquad (2)$$

Where D_{it} is the number of days for which trading volume for stock i in year t is non-zero, and R_{idt} and VD_{idt} are stock i's return and dollar trading volume on day d in year t. Amihud illiquidity is multiplied by one million to avoid scale problems.

Liquidity based on transaction costs - Bid-Ask spread (BAS)

The bid-ask spread is a measure of liquidity of firms' securities that was proposed by Demsetz (1968). Relative bid-ask spreads are calculated for each stock as the yearly average of the daily ask price minus the daily bid price divided by daily the quote mid-point (Amihud & Mendelson, 1986). Research on bid-ask spreads suggests that the spread is comprised of three types of costs facing the dealer: order-processing costs, inventory holding costs and adverse selection costs. The bid-ask spread addresses the adverse selection problem that arises from transacting in firm shares in the presence of asymmetrically informed investors. Less information asymmetry implies less adverse selection, which implies in turn a smaller bid-ask spread and high liquidity (Handa, Schwartz, & Tiwari, 1998). The adverse selection component of the spread was first discussed in (Bagehot, 1971). More recently, Copeland and Galai (1983), Glosten and Milgrom (1985) and Easley and O'hara (1987) develop theoretical models that link information flows to bid-ask spreads.

$$BASR_{it} = \frac{1}{D_{it}}\sum\nolimits_{d=1}^{D_{it}} \frac{ASK_{it} - BID_{it}}{(ASK_{it} + BID_{it})/2} \qquad (3)$$

Where $\mathrm{ASK_{it}}$ the best (lowest) bid price of selling for stock I in period t, $\mathrm{BID_{it}}$ the best (highest) the bid price of buying fore stock I in period t, $\mathrm{D_{it}}$ the number of days of the year t in which the bid prices are available.

Free Floating ratio measure (FFR)

Free float, also known as public float, refers to the shares of a company that can be publicly traded and are not restricted (i.e., held by insiders). In other words, the term is used to describe the number of shares that is available to the public for trading in the secondary market. The free float percentage, also known as float percentage of total shares outstanding, simply shows the percentage of shares outstanding that trade freely. The free float of a stock is closely looked at by investors and is an important metric when picking stocks. Generally, stocks with a small free float are seldom invested in by institutional investors. This is because such stocks are typically more volatile than a stock with a large float. In addition, stocks with a small float generally show a wider bid-ask spread and limited liquidity due to the limited availability of shares in the market. The independent variable, free float ratio (FFR) is defined as the ratio of the total nominal value of publicly traded shares to the total nominal value of all shares of a firm:

$$FFR_{it} = \frac{total\ nominal\ value\ of\ publicly\ traded\ shares}{Total\ nominal\ value\ of\ all\ shares} \qquad (4)$$

Liquidity Index (LIQ-I)

Four liquidity criteria have been used to calculate the combined criterion. If the ratio of the company's stock circulation is greater than the median of the companies, the number one and otherwise the number accepts zero. If the company's non-liquidity is less than the median of the companies, the number one and otherwise the number zero accepts. If the gap in the bid price of the company is greater than the median of the companies, the number one and otherwise the number zero accepts. If the percentage of free floating shares of the company is greater than the median of the companies, the number one and otherwise the number zero accepts. Finally, all criteria are gathered together and divided by the number of criteria.

Independent Variable - Probability of informed trading model (PIN)

We now describe a methodology for estimating the risk of private information based trading. This approach uses a structural microstructure model to formalize the learning problem confronting a market maker in a world with informed and uninformed traders. In a series of papers, Easley et al demonstrate how such models can be estimated using trade data to determine the probability of information-based trading, or PIN, for specific stocks. The rest of this section sets out this approach, drawing heavily from Easley et al. (2002). Microstructure models depict trading as a game between the market maker and traders that is repeated over trading days i=1, I. First, nature chooses whether there is new information at the beginning of the trading day, and these events occur with probability α. The new information is a signal regarding the underlying asset value, where good news is that the asset is worth$\overline{V}_i$, and bad news is that it is worth $\underline{V}_i$. Good news occurs with probability (1-δ) and bad news occurs with the remaining probability, δ. Trading for day i then begins with traders arriving according to Poisson processes throughout the day. The market maker sets prices to buy or sell at each time t in [0, T] during the day, and then executes orders as they arrive. Orders from informed traders arrive at rate μ (on information event days), orders from uninformed buyers arrive at rate ε_b and orders from uninformed sellers arrive at rateε_s. Informed traders buy if they have seen good news and sell if they have seen bad news. If an order arrives at time t, the market maker observes the trade (either a buy or a sale), and he uses this information to update his beliefs. New prices are set, trades evolve, and the price process moves in response to the market maker's changing beliefs. The structural model described above allows us to relate observable market outcomes (i.e. buys or sells) to the unobservable information and order processes that underlie trading. The likelihood function for trade on a single trading day that is implied by this model is

$$L(\theta|(B_i,S_i)) = \alpha(1-\delta)e^{-(\mu+\varepsilon_b)}\frac{(\mu+\varepsilon_b)^{B_i}}{B_i!}e^{-\varepsilon_s}\frac{\varepsilon_s^{S_i}}{S_i!} + \alpha\delta e^{-\varepsilon_b}\frac{\varepsilon_b^{B_i}}{B_i!}e^{-(\mu+\varepsilon_s)}\frac{(\mu+\varepsilon_s)^{S_i}}{S_i!} + (1-\alpha)e^{-\varepsilon_b}\frac{\varepsilon_b^{B_i}}{B_i!}e^{-\varepsilon_s}\frac{\varepsilon_s^{S_i}}{S_i!} \quad (5)$$

where B and S represent total buy trades and sell trades for the day respectively, and θ = (α, μ, ε_b, ε_s, δ) is the parameter vector. This likelihood is a mixture of distributions where the trade outcomes are weighted by the probability of it being a "good news day" α (1−δ), a "bad news day" (αδ), and a "no-news day" (1−α). Imposing sufficient independence conditions across trading days gives the likelihood function across I days

$$V = L(\theta|M) = \prod_{i=1}^{I} L(\theta|B_t,S_t) \quad (6)$$

where (B_i, S_i) is trade data for day i = 1,…,I and M=((B_1,S_1), …,(B_I,S_I)) is the data set. Maximizing (4) over θ given the data M thus provides a way to determine estimates for the underlying structural parameters of the model (i.e. α, μ,ε_b,ε_s, δ). This model allows us to use observable data on the number of buys and sells per day to make inferences about unobservable information events and the division of trade between the informed and uninformed. In effect, the model interprets the normal level of buys and sells in a stock as uninformed trade, and it uses this data to identify the rates of uninformed order flow, ε_b andε_s. Abnormal buy or sell volume is interpreted as information-based trade, and it is used to identify μ. The number of days in which there is abnormal buy or sell volume is used to identify α and δ. Of course, the maximum likelihood actually does all of this simultaneously. The estimation of the model's structural parameters can be used to construct the probability that an order is from an informed trader, known as a PIN. In particular, given some history of trades, the market maker can estimate the probability that the next trade is from an informed trader. It is straightforward to show that the probability that the opening trade is information-based is given by

$$PIN_{it} = \frac{\alpha\mu}{\alpha\delta + 2\varepsilon} \quad (7)$$

Where αμ + ε_b+ ε_s is the arrival rate for all orders and αμ is the arrival rate for information-based orders. PIN is thus a measure of the fraction of orders that arise from informed traders relative to the overall order flow (Aslan, Easley, Hvidkjaer, & O'hara, 2011).

We classify trades as buys and sells using the technique developed by C. M. Lee and Ready (1991). Trades at prices above the midpoint of the bid and ask are called buys; those below the midpoint are called sells. For trades executed at the bid-ask midpoint, we classify trades executed at a price higher than the previous trade as buys and those executed at a lower price as sells.

Control Variables

In regression analysis, we control for a variety of variables that may affect stock liquidity.

Company Size (CS): Firm size is measured by market value of equity, computed as the number of shares outstanding multiplying the fiscal year-end share price. Higher stock liquidity is expected for larger firms (Atiase, 1985; Freeman, 1987). Consequently, we anticipate a positive association between firm size and stock liquidity.

Company Growth Opportunity (M/B): Growth Opportunity is measured by market value of equity, computed as the number of shares outstanding multiplying the fiscal year-end share price, divided by the book value of equity. Higher stock liquidity is expected for more firms Growth opportunity. Consequently, we anticipate a positive association between firm growth opportunity and stock liquidity.

Debt ratio (DR): Debt ratio is measured by book value of total debts divided by the book value of total assets. Lower stock liquidity is expected for higher firm debt ratio. Consequently, we anticipate a negative association between debt ratio and stock liquidity.

Return on equity (ROE): Return on equity is measured by net profit after tax divided by the book value of equity. Higher stock liquidity is expected for higher firm Return on equity. Consequently, we anticipate a positive association between Return on equity and stock liquidity.

Company Loss (CL): Another control variable is loss, a dummy variable equaling one if a firm's current annual net income is negative and zero otherwise. Previous literature indicates that loss firms have higher bid-ask spreads than profitable firms (Brown, Hillegeist, & Lo, 2009; Ng, 2007; Wittenberg-Moerman, 2008). Lower stock liquidity is expected for higher firm Loss. Consequently, we anticipate a negative association between Firm Loss and stock liquidity.

Volatility of Operational Cash Flow (OCFV): This variable measured as the standard deviation of cash flow from operations scaled by total assets over the previous five years. Lower stock liquidity is expected for higher firm Volatility of Operational Cash Flow. Consequently, we anticipate a negative association between Volatility of Operational Cash Flow and stock liquidity.

Volatility of Stock Returns (SRV): the standard deviation of the closing returns in the past 60 months. Lower stock liquidity is expected for higher firm Volatility of Stock Returns. Consequently, we anticipate a negative association between Volatility of Stock Returns and stock liquidity.

3.3. Empirical models

To examine the relation between probability of informed trading and stock liquidity, we employ the following regression:

$$LIQ_{it} = \beta_0 + \beta_1 PIN_{it} + \sum_{j=1}^{7} \beta_j controls_{it} + \varepsilon_{it} \qquad (8)$$

$$STOR_{it} = \beta_0 + \beta_1 PIN_{it} + \sum_{j=1}^{7} \beta_j controls_{it} + \varepsilon_{it} \qquad (9)$$

$$ILLIQ_{it} = \beta_0 + \beta_1 PIN_{it} + \sum_{j=1}^{7} \beta_j controls_{it} + \varepsilon_{it} \qquad (10)$$

$$BASR_{it} = \beta_0 + \beta_1 PIN_{it} + \sum_{j=1}^{7} \beta_j controls_{it} + \varepsilon_{it} \qquad (11)$$

$$FFR_{it} = \beta_0 + \beta_1 PIN_{it} + \sum_{j=1}^{7} \beta_j controls_{it} + \varepsilon_{it} \qquad (12)$$

$$LIQ\_I_{it} = \beta_0 + \beta_1 PIN_{it} + \sum_{j=1}^{7} \beta_j controls_{it} + \varepsilon_{it} \qquad (13)$$

In the model (8), the dependent variable LIQ, is measured by STOR, ILLIQ, BASR, FFR, LIQ_I. Our primary independent variable is PIN as discussed above. We control Company Size (CS), Company Growth Opportunity (M/B), Debt ratio (DR), Return on equity (ROE), Company Loss (CL), Volatility of Operational Cash Flow (OCFV), Volatility of Stock Returns (SRV). In all regressions, we include industry and year dummies to control for industry and year fixed effects. Detailed variable definitions are given in the above.

4. Empirical results

4.1. Descriptive statistics

We start our descriptive analysis by providing summary statistics for the variables used in our empirical models, as shown in Table 1. Table 1 reports the summary statistics for the major variables used in our main regression models. The means of the Five Stock Liquidity measures, STOR, ILLIQ, BASR, FFR, LIQ_I, are Positive 0.192, 0.169, 0.028, 0.199, and 0.496, respectively. The mean of PIN is Positive 0.1. The mean of OCFV is 0.086. The mean of SRV is 0.98. The mean of CS is 6.094. The mean of CG is 2.65. The mean of DR is 0.618. The mean of ROE is 0.297. The mean of LIQ_I is 0.496, respectively. The results show that 14.8% of the Firms reported losses.

We then move on to the univariate analysis of the main variables used in our models. Table 2 presents the correlation matrix (Pearson correlation coefficients) for the variables used in our main regression models. The correlation coefficients show a significantly positive association between STOR and BASR, FFR, LIQ_I, a significantly negative association between ILLIQ and BASR, FFR, LIQ_I, a significantly positive association between BASR and FFR, LIQ_I, a significantly positive association between FFR and LIQ_I, a significantly positive association between PIN and STOR, ILLIQ, BASR, LIQ_I. Such relationships provide great support for constructs and measures of this study.

We winsorized all continuous variables at the 1st and 99th percentiles because the estimation of ordinary least squares (OLS) could be susceptibly influenced by outlying observations (Wooldridge, 2016). We used both Pearson correlations to investigate the likelihood of multicollinearity. Table 2 reports that the correlation values among all variable used in the model and the pairwise correlations for the independent and control variables are all below 0.7. We also calculated variance inflation factor (VIF) values and the results (not tabulated in the paper) are all less than the critical value of 10 (Gujarati, 2003). Accordingly, we confirm that there is no multicollinearity threat to these variables.

Table 1. Summary statistics

Variable		Mean	Median	Max	Min	Std. Dev.
STOR	(1)	0.192	0.079	0.789	0.009	0.228
ILLIQ	(2)	0.169	0.039	1.511	0.002	0.358
BASR	(3)	0.028	0.029	0.044	0.007	0.011
FFR	(4)	0.199	0.176	0.501	0.021	0.133
LIQ-I	(5)	0.496	0.5	1	0	0.348
PIN	(6)	0.1	0.078	0.251	0.021	0.07
OCFV	(7)	0.086	0.079	0.181	0.027	0.041
SRV	(8)	0.98	0.851	2.295	0.234	0.567
CS	(9)	6.094	6.037	7.356	5.055	0.574
CG	(10)	2.65	2.345	6.675	0.011	1.66
DR	(11)	0.618	0.628	0.974	0.27	0.188
ROE	(12)	0.297	0.285	0.845	-0.293	0.297
CL	(13)	-	-	1	0	-

Note: table 1 reports descriptive statistics on a sample of 113 Tehran-listed companies from 2012 to 2016. STOR is the annual average of stock Turnover Ratio. It is defined as the ratio of the number of shares traded (trading volume) to the number of shares outstanding for a company, ILLIQ is the annual average of Amihud illiquidity ratio, and the "illiquidity" measure proposed by Amihud (2002) is defined as the average ratio of the daily absolute return to trading volume on that day. BASR is the annual average of bid-ask spread ratio, Relative bid-ask spreads are calculated for each stock as the yearly average of the daily ask price minus the daily bid price divided by daily the quote mid-point, FFR is the free float ratio, LIQ-I is the liquidity index, PIN denotes a probability of information based trades defined in Easley et al. (2002)., OCFV is the operational cash flow volatility, measured as the standard deviation of annual cash flow from operations scaled by total assets over the previous five years, SRV is the stock return volatility, calculated as the standard deviation of annual returns over the previous five years, CS is the company size, calculated as the natural logarithm of year-end market value of equity, CG is the company Growth Opportunity, calculated as the market value of equity divided by the book value of equity, DR, is the debt ratio, calculated as the total debt scaled by lagged total assets, ROE, is the Return on equity, calculated as net income scaled by average total equity, CL, is the a dummy variable that takes the value one if the company reports a loss and zero otherwise. We also add year level and industry level control variables in our study.

Table 2. Pearson and Spearman correlation matrix.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
(1)	1	-0.14***	0.69***	0.6***	0.76***	0.3***	-0.08**	0.17***	-0.33***	-0.17***	0.16***	-0.26***	0.23***
(2)	-0.05	1	-0.35***	-0.19***	-0.5***	0.12***	-0.02	-0.04	-0.55***	-0.03	0.21***	-0.11**	0.01
(3)	0.59***	-0.25***	1	0.46***	0.77***	0.16***	-0.04	0.21***	-0.02	-0.17***	0.08**	-0.02***	0.16***
(4)	0.62***	-0.003	0.41***	1	0.68***	0.12***	-0.03	0.04	-0.17***	-0.24***	-0.01	-0.2***	0.18***
(5)	0.67***	-0.23***	075***	0.64***	1	0.16***	-0.05	0.13***	0.01	-0.16***	0.02	-0.17***	0.16***
(6)	0.14***	0.2***	013***	0.08	0.12***	1	0.01	0.05	0.03	0.12***	-0.01	0.06	0.01
(7)	-0.07	0.008	-0.04	-0.04	-0.06	-0.01	1	0.02	0.06	0.17***	0.09**	-0.02	0.01
(8)	0.22***	-0.02	-0.19***	0.1**	0.13***	0.08*	0.04	1	0.07	0.23***	0.01	-0.03	0.02
(9)	-0.27***	-0.23***	0.05	-0.16***	0.02	0.008	0.05	-0.01	1	0.35***	-0.24***	0.35***	-0.17***
(10)	-0.17***	0.005	-0.14***	-0.22***	-0.14***	0.09**	0.19***	0.19***	0.31***	1	0.01	0.34***	-0.19***
(11)	0.15***	0.14***	0.08**	-0.005	0.03	-0.003	0.08*	-0.02	-0.24***	0.04	1	-0.27***	0.31***
(12)	-0.3***	0.04	-0.2***	-0.21***	-0.17***	0.06	-0.03	-0.02	0.33***	0.28***	-0.27***	1	-0.3***
(13)	0.27***	0.06	0.15***	0.18***	0.17***	0.004	0.01	0.02	-0.16***	-0.16***	0.33***	-0.37***	1

Note: Table 2 presents the Pearson–Spearman (below and above the diagonal, respectively) correlation matrix of the major variables in 2012–2016. ***, **, and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

4.2. Multivariate analysis

Table 3 shows the baseline regression results for our equation (8). Table 3 reports OLS regressions that examine The Effect of probability of informed trading on stock liquidity. We used a combination of year, industry and year dummies in our OLS and Fixed effect models to avoid heteroscedasticity among industry as well as firm.

Table 3. The Effect of probability of informed trading on stock liquidity

	Column (1) ***STOR***	**Column (2)** ***ILLIQ***	**Column (3)** ***BASR***	**Column (4)** ***FFR***	**Column (5)** ***LIQ-I***
Intercept	-0.02** (-2.15)	0.94*** (3.32)	-0.05*** (-5.21)	0.14** (2.47)	-0.83*** (-3.17)
PIN	0.11*** (4.18)	0.99*** (4.49)	0.001 (0.39)	0.02 (1.5)	0.02 (1.5)
OCFV	0.15** (2.06)	0.08 (0.19)	0.03** (2.11)	0.11*** (5.96)	0.01 (0.08)
SRV	0.03*** (6.27)	-0.03 (-0.8)	0.002** (2.11)	-0.003 (-0.85)	0.04*** (3.76)
CS	0.03*** (3.77)	-0.08*** (-3.83)	0.006*** (9.08)	0.006 (1.42)	0.11*** (6.41)
CG	-0.004 (-1.2)	0.01 (0.75)	-0.001*** (-4.04)	0.001 (0.64)	-0.01*** (-3.4)
DR	-0.06** (-2.31)	0.2*** (3.14)	-0.001 (-0.13)	-0.05*** (-3.71)	-0.37*** (-6.83)
ROE	0.08*** (3.6)	0.18*** (2.77)	-0.002 (-1.32)	-0.002 (-0.29)	0.01 (0.53)
CL	0.04* (1.79)	0.05 (0.85)	0.002 (1.49)	0.04*** (7.86)	0.06*** (2.73)
Year fixed effects	Yes	yes	yes	Yes	yes
Industry fixed effects	Yes	yes	yes	Yes	yes
Adjusted R^2	0.88	0.11	0.73	0.97	0.89

Note: The t-statistics reported in parentheses are based on standard errors clustered by both firm and year. ***, **, and * indicate statistical significance at the 1%, 5% and 10% levels, respectively. All regressions include industry and year fixed effects. All continuous variables are winsorized at the top and bottom 1%. We apply the Fisher test of homogeneity to accept or reject the use of panel data model. The results of this test, not reported here, show the existence of an Individual effect and accept the use of panel data model regression. Fixed effect estimation selected by Hausman test to determine fixed effect or random effect. We also add year level and industry level control variables in our study.

Table 3 presents the impact of probability of informed trading on stock liquidity. The first column of table 3 reports the results of estimating Eq. (8) using STOR as the dependent variable. As shown in the first column, the coefficient of PIN is statistically significant at the 1% level, indicating that there is a positive relationship probability of informed trading and stock liquidity. This result supports our hypothesis of a significant relationship between probability of informed trading and turnover measure. The second column of table 3 reports the regressions results with ILLIQ as the dependent variables. The coefficients of PIN continue to be positive and significant at the 1% level after controlling for a series of variables as discussed in Section 3.2. This result supports our hypothesis of a significant relationship between probability of informed trading and Amihud's illiquidity measure. It suggests that the Negative relationship between probabilities of informed trading and stock liquidity. Columns (3)-(5) of Table 3 report the regressions results with BASR, FFR, and LIQ_I as the dependent variables. The coefficients of PIN are Positive 0.001, Positive 0.02 and negative 0.14, which is not insignificant.

5. Conclusions

We investigated the relationship between probability of informed trading and stock liquidity. Prior studies show that the quality of disclosure increases stock liquidity by affecting the amount of information asymmetry (probability of informed trading) in the distribution of information among managers of companies and investors by reducing the trading cost and ultimately leads to a reduction in cost of capital through reducing information risk. Note that O'Hara (2003) argues that the cost of equity will be higher when there is more information asymmetry in capital markets and liquidity will be less among traded stocks. Specifically, we use a sample of 565 firm-year observations of Tehran-listed companies between 2012 and 2015. Our findings show that the association between probability of informed trading and stock liquidity (Stock Turnover) is positive, which supports the findings of Stoll (1978). Furthermore, a significant relationship between probability of informed trading and stock liquidity (Amihud's illiquidity measure) is positive, which supports the findings of Amihud et al. (2005), Amihud et al. (2013), and Amihud et al. (2015). In this paper I predict a direct relation between probability of informed trading (inverse relation between firms' disclosure policies) and Stock Turnover and bid-ask spreads. In addition, increased trading by informed traders and higher probability of information event occurrence are predicted both to increase Amihud's illiquidity. Nevertheless, we find no significant relation probability of informed trading and Bid-Ask spread (adverse selection component of information asymmetry). This is consistent with Botosan and Frost (1998). Our findings is consistent with theory of Amihud and Mendelson (1986), who evidence shows that expected return is an increasing function of asset illiquidity because investors want to be compensated for holding less liquid assets. This compensation is different from the compensation that investors require for bearing risk about asset value.

The results show a positive relationship between the extent of probability of informed trading and market liquidity suggesting that an Information asymmetry between informed and uninformed traders is likely to improve stock market liquidity resulting from increased trading volumes. The findings also show a positive relationship between the extent of probability of informed trading and Amihud’s (2002) measure (is one of the best price impact proxies) an increase in the adverse selection component of the spread. This finding suggests that information device is crucial to help reducing adverse selection and then the gap between investors. The decomposition of the total score into sub-indices shows that non-financial and financial information are important in trading decisions. Strategic information may be attractive for long-term positions. Our findings suggest that the Information asymmetry between informed and uninformed traders is worth considering when discussing the determinants of stock liquidity. The liquidity of a security declines when investors suspect that insiders are trading on privileged information. A supplementary policy that improves the information quantity of firms, for example, mandating more timely and detailed information disclosures, might help change that information environment and improve the effectiveness of the liquidity in the long run.

Like other survey studies, this current study has some limitations. First is the measure of stock liquidity and Information asymmetry between informed and uninformed traders. Here stock liquidity is measured through five indicators i.e. Turnover Ratio, Amihud illiquidity, Bid-Ask spread, Free Floating ratio, Liquidity Index and Information asymmetry between informed and uninformed traders is measured with pin EHO model. Although the intuition behind the choice of indicators is sound, there are many other variables that may also represent stock liquidity and pin. Further research may wish to look at other indicators to enhance the literature on stock liquidity and could extend the models we used to pin. Second is the sample selection. Our sample size is relatively small due to the data availability which affects the generalization of our findings.

References

1) Ajina, A., Sougne, D., & Lakhal, F. (2015). Corporate disclosures, information asymmetry and stock-market liquidity in France. *Journal of Applied Business Research (JABR), 31*(4), 1223-1238.
2) Akerlof, G. A. (1970). The Market for “Lemons”: Quality Uncertainty and the Market Mechanism. *The quarterly journal of economics, 84*(3), 488-500. doi: 10.2307/1879431
3) Amihud, Y. (2002). Illiquidity and stock returns: cross-section and time-series effects. *Journal of financial markets, 5*(1), 31-56. doi: https://doi.org/10.1016/S1386-4181(01)00024-6
4) Amihud, Y., & Mendelson, H. (1986). Asset pricing and the bid-ask spread. *Journal of Financial Economics, 17*(2), 223-249.
5) Amihud, Y., Hameed, A., Kang, W., & Zhang, H. (2015). The illiquidity premium: International evidence. *Journal of Financial Economics, 117*(2), 350-368.
6) Amihud, Y., Mendelson, H., & Pedersen, L. H. (2005). Liquidity and Asset Prices. now: Boston.
7) Amihud, Y., Mendelson, H., & Pedersen, L. H. (2013). Market liquidity. *Cambridge Books*.
8) Aslan, H., Easley, D., Hvidkjaer, S., & O'hara, M. (2011). The characteristics of informed trading: Implications for asset pricing. *Journal of Empirical Finance, 18*(5), 782-801.
9) Atiase, R. K. (1985). Predisclosure information, firm capitalization, and security price behavior around earnings announcements. *Journal of Accounting Research*, 21-36.
10) Bagehot, W. (1971). The only game in town. *Financial Analysts Journal, 27*(2), 12-14.

11) Baker, M., & Stein, J. C. (2004). Market liquidity as a sentiment indicator. *Journal of financial markets, 7*(3), 271-299.
12) Balasemi, N., Veiseh, S. M., & Malgharani, A. M. (2015). Relationship between liquidity and stock returns considering company's life cycle: The case study of Tehran stock exchange listed companies. *WALIA Journal, 31*, 85-91.
13) Barney, J. (1991). Firm resources and sustained competitive advantage. *Journal of management, 17*(1), 99-120.
14) Bergh, D. D., Ketchen Jr, D. J., Orlandi, I., Heugens, P. P., & Boyd, B. K. (2019). Information asymmetry in management research: Past accomplishments and future opportunities. *Journal of management, 45*(1), 122-158.
15) Black, F. (1971). Toward a fully automated stock exchange, part I. *Financial Analysts Journal, 27*(4), 28-35.
16) Botosan, C., & Frost, C. (1998). Regulation, disclosure and market liquidity. *Unpublished working paper, Washington University*.
17) Brennan, M. J., Chordia, T., Subrahmanyam, A., & Tong, Q. (2012). Sell-order liquidity and the cross-section of expected stock returns. *Journal of Financial Economics, 105*(3), 523-541.
18) Brown, S., & Hillegeist, S. A. (2007). How disclosure quality affects the level of information asymmetry. *Review of Accounting Studies, 12*(2-3), 443-477.
19) Brown, S., Hillegeist, S. A., & Lo, K. (2009). The effect of earnings surprises on information asymmetry. *Journal of Accounting and Economics, 47*(3), 208-225.
20) Chai, D., Faff, R., & Gharghori, P. (2010). New evidence on the relation between stock liquidity and measures of trading activity. *International Review of Financial Analysis, 19*(3), 181-192.
21) Copeland, T. E., & Galai, D. (1983). Information effects on the bid-ask spread. *The Journal of Finance, 38*(5), 1457-1469.
22) Datar, V. T., Naik, N. Y., & Radcliffe, R. (1998). Liquidity and stock returns: An alternative test. *Journal of financial markets, 1*(2), 203-219.
23) Demsetz, H. (1968). The cost of transacting. *The quarterly journal of economics, 82*(1), 33-53.
24) Diamond, D. W., & Verrecchia, R. E. (1991). Disclosure, liquidity, and the cost of capital. *The Journal of Finance, 46*(4), 1325-1359.
25) Easley, D., & O'hara, M. (1987). Price, trade size, and information in securities markets. *Journal of Financial Economics, 19*(1), 69-90.
26) Easley, D., & O'Hara, M. (1992). Adverse selection and large trade volume: The implications for market efficiency. *Journal of Financial and Quantitative Analysis*, 185-208.
27) Easley, D., Hvidkjaer, S., & O'hara, M. (2002). Is information risk a determinant of asset returns? *The Journal of Finance, 57*(5), 2185-2221.
28) Easley, D., Kiefer, N. M., & O'Hara, M. (1997a). The information content of the trading process. *Journal of Empirical Finance, 4*(2-3), 159-186.
29) Easley, D., Kiefer, N. M., & O'Hara, M. (1997b). One day in the life of a very common stock. *The Review of Financial Studies, 10*(3), 805-835.
30) Easley, D., Kiefer, N. M., O'hara, M., & Paperman, J. B. (1996). Liquidity, information, and infrequently traded stocks. *The Journal of Finance, 51*(4), 1405-1436.
31) Engle, R. F., & Russell, J. R. (1998). Autoregressive conditional duration: a new model for irregularly spaced transaction data. *Econometrica*, 1127-1162.
32) Fong, K. Y., Holden, C. W., & Trzcinka, C. A. (2017). What are the best liquidity proxies for global research? *Review of Finance, 21*(4), 1355-1401.
33) Freeman, R. N. (1987). The association between accounting earnings and security returns for large and small firms. *Journal of Accounting and Economics, 9*(2), 195-228.
34) Glosten, L. R., & Harris, L. E. (1988). Estimating the components of the bid/ask spread. *Journal of Financial Economics, 21*(1), 123-142.
35) 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.
36) Goyenko, R. Y., Holden, C. W., & Trzcinka, C. A. (2009). Do liquidity measures measure liquidity? *Journal of Financial Economics, 92*(2), 153-181.
37) Grossman, S. J., & Stiglitz, J. E. (1980). On the impossibility of informationally efficient markets. *The American economic review, 70*(3), 393-408.
38) Handa, P., Schwartz, R. A., & Tiwari, A. (1998). The ecology of an order-driven market. *Journal of Portfolio Management, 24*(2), 47-+.

39) He, Y., Wang, J., & Wei, K. J. (2011). Do bond rating changes affect the information asymmetry of stock trading? *Journal of Empirical Finance, 18*(1), 103-116.
40) Healy, P. M., & Palepu, K. G. (2001). Information asymmetry, corporate disclosure, and the capital markets: A review of the empirical disclosure literature. *Journal of Accounting and Economics, 31*(1-3), 405-440.
41) Jacoby, G., Fowler, D. J., & Gottesman, A. A. (2000). The capital asset pricing model and the liquidity effect: A theoretical approach. *Journal of financial markets, 3*(1), 69-81.
42) Jensen, M. C., & Meckling, W. H. (1976). Theory of the firm: Managerial behavior, agency costs and ownership structure. *Journal of Financial Economics, 3*(4), 305-360.
43) Kim, O., & Verrecchia, R. E. (1994). Market liquidity and volume around earnings announcements. *Journal of Accounting and Economics, 17*(1-2), 41-67.
44) Kurlat, P. (2018). Liquidity as social expertise. *The Journal of Finance, 73*(2), 619-656.
45) Kyle, A. S. (1985). Continuous auctions and insider trading. *Econometrica: Journal of the Econometric Society*, 1315-1335.
46) Lee, C. F., & Lee, J. C. (2015). *Handbook of financial econometrics and statistics*: Springer.
47) Lee, C. M., & Ready, M. J. (1991). Inferring trade direction from intraday data. *The Journal of Finance, 46*(2), 733-746.
48) Lee, C. M., & Yahn, T. L. (1997). Accounting Informotion and Bid-Ask Spreads. *Accounting horizons, 11*(4), 50-60.
49) Lesmond, D. A. (2005). Liquidity of emerging markets. *Journal of Financial Economics, 77*(2), 411-452.
50) Leuz, C., & Verrecchia, R. E. (2000). The economic consequences of increased disclosure. *Journal of Accounting Research*, 91-124.
51) Liu, W. (2006). A liquidity-augmented capital asset pricing model. *Journal of Financial Economics, 82*(3), 631-671.
52) Marshall, B. R., Nguyen, N. H., & Visaltanachoti, N. (2012). Commodity liquidity measurement and transaction costs. *The Review of Financial Studies, 25*(2), 599-638.
53) McNichols, M., & Trueman, B. (1994). Public disclosure, private information collection, and short-term trading. *Journal of Accounting and Economics, 17*(1-2), 69-94.
54) Naik, P., & Reddy, Y. (2021). Stock Market Liquidity: A Literature Review. *SAGE Open, 11*(1), 2158244020985529.
55) Ng, J. (2007). Earnings surprises and changes in liquidity. *Available at SSRN 889133*.
56) O'Hara, M. (2003). Presidential address: Liquidity and price discovery. *The Journal of Finance, 58*(4), 1335-1354.
57) Ojah, K., Muhanji, S., & Kodongo, O. (2020). Insider trading laws and price informativeness in emerging stock markets: The South African case. *Emerging Markets Review*, *43*, 100690.
58) Pástor, Ľ., & Stambaugh, R. F. (2003). Liquidity risk and expected stock returns. *Journal of Political economy, 111*(3), 642-685.
59) Pfeffer, J., & Salancik, G. R. (1978). Social control of organizations. *The external control of organizations: A resource dependence perspective*, 39-22.
60) Powell, W. W., & DiMaggio, P. J. (2012). *The new institutionalism in organizational analysis*: University of Chicago press.
61) Simsir, S. A., and K. Simsek. 2018. "Measuring the Market Impact of Private Information: The Curious Case of Corporate Announcements in Turkey." *Working Paper, Sabanci University, Sabanci School of Management.*
62) Spence, M. (1978). Job market signaling *Uncertainty in economics* (pp. 281-306): Elsevier.
63) Stoll, H. R. (1978). The supply of dealer services in securities markets. *The Journal of Finance, 33*(4), 1133-1151.
64) Welker, M. (1995). Disclosure policy, information asymmetry, and liquidity in equity markets. *Contemporary accounting research, 11*(2), 801-827.
65) Williamson, O. E. (1975). Markets and hierarchies: analysis and antitrust implications: a study in the economics of internal organization. *University of Illinois at Urbana-Champaign's Academy for Entrepreneurial Leadership Historical Research Reference in Entrepreneurship*.
66) Wittenberg-Moerman, R. (2008). The role of information asymmetry and financial reporting quality in debt trading: Evidence from the secondary loan market. *Journal of Accounting and Economics, 46*(2-3), 240-260.

67) Zucker, L. G. (1987). Institutional theories of organization. *Annual review of sociology*, *13*(1), 443-464.