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Individual Traders, Informed Trading, and Stock Market Liquidity

Abstract

Purpose: This study examines the relationship between individual trading intensity and stock liquidity, assessing whether individual traders are informed or merely noise traders. We aim to understand individual trading's impact on liquidity in an emerging market setting without market makers.

Study design/methodology/approach: We use a comprehensive dataset from intraday individual trading activity across all listed companies in Boursa Kuwait, employing regression models with industry and time fixed effects, different liquidity and probability of informed trading measures, and a Heckman two-stage selection model to control for self-selection bias.

Sample and data: The sample includes all listed firms on Boursa Kuwait between January 2013 and December 2018.

Results: We have found a significant negative relationship between individual trading intensity and stock liquidity, with higher individual trading associated with lower returns and a lower probability of informed trading (PIN). These findings suggest that individual traders often act as noise traders, increasing liquidity demand and causing price distortions.

Originality/value: This study uniquely examines individual trading intensity in a market without market makers, removing the confounding effects of intermediary liquidity providers. Our findings, which reveal the direct impacts of individual trading on liquidity, enhance the literature on noise trading and market efficiency, especially in similar emerging markets.

Research limitations/implications: The study is limited to the period before 2019, prior to the introduction of market makers in Boursa Kuwait. This provides a clean analysis but may not reflect the dynamics of mature markets with active market makers. The findings are crucial for stock exchanges focusing on liquidity enhancement programs.

Keywords: Liquidity, Informed Trading, Market Efficiency, Individual Traders.
JEL classification: G21, G28, G14, E5

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الملخص

المتداولون الأفراد، تداول المطلعين، وسيولة أسواق الأسهم

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هدف الدراسة: تتناول هذه الدراسة العلاقة بين كثافة تداول الأفراد وسيولة الأسهم، مع التركيز على مدى إمكانية تصنيف المتداولين الأفراد كمستثمرين مطّلعين أو كمتداولين عشوائيين. وتهدف الدراسة إلى المساهمة في فهم تأثير تداول الأفراد على السيولة في سوق مميز يخلو من صناع السوق.
تصميم/ منهجية/ طريقة الدراسة: تستخدم الدراسة مجموعة بيانات شاملة وغير منحازة لأنشطة التداول اليومية للأفراد، تغطي جميع الشركات المدرجة في بورصة الكويت. وتعتمد الدراسة على نماذج الانحدار مع الأخذ بالاعتبار التأثيرات الثابتة الناجمة عن الزمن والقطاع، بالإضافة إلى مقاييس مختلفة للسيولة واحتمالية التداول المطلع (PIN)، ونموذج Heckman المكون من مرحلتين للتحكم في احتمالية الانحياز الذاتي في العينة.
عينة الدراسة وبياناتها: تشمل العينة جميع الشركات المدرجة في بورصة الكويت خلال الفترة من يناير 2013 إلى ديسمبر 2018.
نتائج الدراسة: تشير نتائج الدراسة إلى علاقة سلبية بين كثافة تداول الأفراد وسيولة الأسهم، حيث ترتبط الأسهم ذات الكثافة التداولية العالية بعوائد أقل واحتمالات منخفضة للتداول المطلع. هذه النتائج تؤكد أن المتداولين الأفراد يميلون للتداول العشوائي مما يزيد الطلب على السيولة ويساهم في تشويه الأسعار.
أصالة الدراسة: تُقدم هذه الدراسة مساهمة فريدة بتحليلها لكثافة تداول الأفراد في سوق بدون صناع سوق، مما يُلغي التأثيرات المشوشة لمزودي السيولة (صناع السوق). كما تساهم النتائج في إثراء الأدبيات المتعلقة بفهم التداول العشوائي للأفراد وكفاءة السوق في الأسواق الناشئة.
حدود الدراسة وتطبيقاتها: تقتصر الدراسة على الفترة التي تسبق عام 2019، حين بدأت بورصة الكويت بإدخال صناع السوق تدريجيًا، مما يتيح القيام بتحليلًا نقيًا قد لا يعكس ديناميكيات الأسواق المتقدمة. نتائج الدراسة تعتبر مهمة لمتخذي القرار لأهميتها في برامج تحسين السيولة واكتشاف السعر.

الكلمات المفتاحية: سيولة الأسهم، تداول المطلعين، كفاء أسواق المال، تداول الأفراد.

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Introduction

After the Great Recession of 2007, stock market participants were reminded that liquidity is a critical component in understanding asset pricing, and that the cost and time of executing trades are essential in assessing stock market performance (Amihud, 2002). The extent to which individuals' trading improves or impedes stock market liquidity is not yet well understood, specifically, the extent to which the change in the proportion of individuals' trading volume to total trading volume (individual trading intensity) affects stock liquidity and informed trading.

The question of how individual trading affects liquidity and price discovery is particularly relevant in unique market environments where institutional structures differ significantly from those of more developed markets. The Kuwaiti stock market provides one such environment, offering a valuable setting to explore these dynamics in greater depth. The domestic stock market in Kuwait dates back to 1952, operating on an over-the-counter basis until the establishment of the Boursa Kuwait (formally called Kuwait Stock Exchange (KSE) between 1983 and 2014). The Capital Market Authority (CMA) is the main regulator overseeing its function, taking on the role of the exchange commission. The number of listed firms ranged between 185 and 215 between the years 2013 and 2018, trading in two parallel markets (Premier and Main Markets), covering 13 different industrial sectors.

Boursa Kuwait is the oldest and fourth-largest stock market in the Arab world, with a total market capitalization value of KD 28.7 billion (approximately USD 93 billion) as of the end of 2018. The market has historically been dominated by banks, which account for roughly half of its market capitalization, and the market turnover ratio has historically hovered between 10 and 15 percent of its total market capitalization. Foreign investors are allowed to trade and comprise approximately 14% of the total trading activity, whereas institutional investors make up roughly 60% of the executed trades as of December 2018. The Kuwaiti market has undergone various improvement programs, culminating in its inclusion in FTSE Russell's Emerging Market Index (2017), S&P DJI Global Equity Index (2018), and MSCI Emerging Market Index (2019). These milestones underscore global recognition of the market development efforts undertaken by Boursa Kuwait and the CMA.[1]

[1] Table 1 highlights the volume of trades of the listed companies, and the total market capitalization of Boursa Kuwait during our sample period.

The Kuwaiti market offers a unique empirical setting for examining the effects of individual trading on liquidity and returns. Prior to 2019, Boursa Kuwait operated without market makers, providing an environment free from artificial liquidity provisioning. This allows us to isolate the impact of individual traders on market outcomes without the confounding effects of market makers. Moreover, the predominance of individual investors in Boursa Kuwait, unlike more institutionally dominated markets, provides a valuable opportunity to study the dynamics of retail trading and its consequences.

Formally, our paper investigates two main hypotheses: First, whether higher individual trading intensity is negatively associated with stock liquidity, as individual traders act as noise traders who demand liquidity and increase price distortions.[2] Second, whether higher individual trading intensity correlates with lower probabilities of informed trading, reflecting reduced informational efficiency in markets dominated by retail activity and the absence of market makers providing stock inventory to enhance liquidity.

To this end, we utilize clean and comprehensive data from Boursa Kuwait, which provides us with an opportunity to examine our research question in a unique setting. Compared to other studies: (1) our intraday stock trading data covers all the listed stocks in the domestic stock market and is not limited to a sample of brokerage firms (e.g., Barber & Odean, 2000; Barber et al., 2008; Graham & Kumar, 2006); (2) we use actual individual trades rather than proxies (Lee & Radhakrishna, 2000); and (3) Given the market structure during the sample period, our setting has no influence of market makers intermediation, who have an affirmative obligation to provide stock liquidity.[3]

[2] Noise trading refers to trading activity driven by factors unrelated to fundamental information, such as sentiment, speculation, or behavioral biases. Unlike informed trading, noise trading can distort prices and reduce market efficiency by introducing unnecessary volatility.

[3] The Capital Market Authority introduced laws allowing the presence of market making in Kuwait in 2015. In August 2019, the Kuwait and Middle East Financial Investment Company (KMEFIC) received approval as the first registered market maker on Boursa Kuwait (see Boursa Kuwait Registers KMEFIC as Market Maker, 2019). However, this does not affect our results, as our data covers the period from January 2014 to December 2018. Recently, Alsabah and Althaqeb (2024) have explored the impact of market makers on liquidity in Boursa Kuwait, highlighting both the opportunities and challenges that have emerged since the introduction of market making.

Table 1
Boursa Kuwait Characteristics

This table reports key characteristics about Boursa Kuwait during our sample period, covering the time frame between January 2013 and December 2018, highlighting the volume of trades executed by the listed companies, and showing the total market capitalization of the stock market.

Year	Trading Volume (Billions KD)	Total Market Capitalization (Billions KD)
2013	11.39	31.15
2014	6.18	30.25
2015	3.94	24.24
2016	2.88	26.24
2017	5.73	27.90
2018	4.13	28.70

We have found that individual trading intensity is associated with a statistically significant negative relationship with stock liquidity, measured by high-low spread and turnover value, after controlling the known liquidity determinants.[4] One of the findings is that individual trading intensity is associated with lower monthly returns. Our results are robust to various model specifications, including industry and year-month fixed effects. To alleviate concerns of possible self-selection bias, we have re-estimated our results using a two stage Heckman (1979) self-selection regression model, and found similar results which indicate that our results are not affected by unobservable factors. Further, using intraday data and PIN, which is calculated based on the methodologies outlined in Yan and Zhang (2012) and Gan et al. (2015), we find that PIN is negatively related to our measure of individual traders' trading intensity, which suggests that individual traders are less informed.

The findings of this paper hold significant policy implications for market design and regulation. By highlighting the adverse effects of individual trading intensity on liquidity and price discovery, our research underscores the need for

[4] Following Corwin and Schultz (2012), we define the high-low spread as the spread between the highest and lowest price of the stock at the end of day divided by the highest price. Stock turnover value is defined as the value of daily shares traded divided by the total number of outstanding shares.

targeted liquidity enhancement programs, such as promoting institutional participation, expediting the market maker's integration, and facilitating a more informed trading culture by individual traders to enhance market efficiency.

Our paper contributes to the growing body of literature surrounding individual traders' roles in providing liquidity, especially in the context of informed trading. While similar patterns of individual traders acting as noise traders have been observed in other markets, the Kuwaiti market's distinctive structure allows for a more isolated analysis of these dynamics. Specifically, Boursa Kuwait is characterized by a predominance of individual investors, with roughly half of the recorded trades belonging to individuals, and the absence of market makers during the study period. This provides a transparent environment to examine the unmediated effects of individual trading intensity on liquidity. This setting enables us to add depth to the established theories by showing how these effects manifest in an emerging market, potentially offering insights relevant to other emerging markets with similar structures. As such, the implications of our study are essential for stock exchanges, given their liquidity enhancement programs.

The remainder of this paper is organized as follows: a review of the literature is provided in the next section, followed by a discussion of our data, variable construction, and methodology. The empirical results are then presented, and the paper concludes with a summary of the findings.

Literature Review

One of the main drivers behind our research question is the inconsistent evidence in the literature regarding the role of individual investors in financial markets. While some studies suggest that individual investors can act as informed traders who contribute to price discovery (e.g., Ivković & Weisbenner, 2005; Kaniel et al., 2012; Kumar & Lee, 2006; Massa & Simonov, 2006), others find that they primarily act as noise traders, leading to reduced liquidity and increased price distortions (e.g., Barber & Odean, 2000; Kelley & Tetlock, 2013). Similarly, while prior research explores whether informed trading improves stock liquidity (e.g., Agudelo et al., 2015; Rindi, 2008), these findings remain inconclusive, particularly in markets dominated by individual investors. Our study directly addresses these gaps by investigating how individual trading intensity influences liquidity and informed trading.

Nonetheless, our study is grounded in established theories on noise trading and liquidity (e.g., Barber & Odean 2000; Rindi 2008) and revisits the hypothesis by questioning whether these theories hold in the unique context of the Kuwaiti market, which lacks market makers and relies heavily on individual traders. This environment presents a rare setting to empirically test the robustness of existing theories, as it removes certain stabilizing market mechanisms, thereby exposing the direct effects of individual trader activity on liquidity and market outcomes. Therefore, our research can offer novel insights, given the absence of market makers, and hence extending existing theories in new ways that contribute to our understanding of market structures.

Market makers play an important role to facilitate a fair and orderly flow of trades as they continuously stand ready to buy shares from traders who wish to sell, and to sell shares to traders who wish to buy, and they serve an important liquidity function in order to stabilize prices (Clark-Joseph et al., 2017; Kedia & Zhou, 2011). But, since market makers set the bid–ask spread by taking into consideration the inventory costs, adverse selection risk, operation cost and required profit (Stoll, 1989), they end up affecting stock market liquidity and influencing order flow; therefore it is difficult to measure or isolate these effects. Hence, our setting is unique in providing a transparent environment where all traders can view the entire order book for a stock, without a designated liquidity provider. This allows us to clearly understand and measure the effects of a stock's trading intensity by individuals on raw stock liquidity and the degree of informed trading.

In line with the theoretical framework of Rindi (2008), we expect that an increase in trading activity by individual traders is consistent with a reduction in market liquidity as uninformed traders act as noise traders who demand liquidity. This is likely explained via the individual traders perceived role as noise traders, since such trades are typically found not to be correlated with firm fundamentals (Peress & Schmidt, 2021). Hence, we expect that stocks with higher individual trading intensity to be characterized by less liquidity and a lower probability of informed trading (PIN).

More recently, some studies in the literature have further explored the roles of retail investors in shaping market liquidity under varying market conditions. For instance, Barber et al. (2022) highlight the growing influence of retail investors during periods of market distress, demonstrating how attention-driven trading impacts asset pricing and liquidity dynamics. Ozik et al. (2021) examine retail trading during the COVID-19 pandemic and find that increased retail activity attenuated liquidity shocks, albeit inconsistently across asset classes and market segments. Similarly, Naik and Reddy (2021) offer a comprehensive review of stock market liquidity, emphasizing the distinct liquidity challenges and opportunities in emerging markets. These studies underscore the significance of retail trading as a double-edged sword. While it can contribute to liquidity provision, it also introduces volatility and inefficiencies, particularly in markets characterized by limited institutional participation.

By situating our findings within this broader context, we aim to bridge the gap between theoretical expectations and empirical evidence across diverse market structures, thereby extending the relevance of our study to other emerging and developed markets. These theoretical expectations suggest that individual trading intensity can undermine market efficiency, especially in settings with limited institutional participation and no market makers. Examining these dynamics in the context of Boursa Kuwait not only addresses the mixed evidence in the literature, but it also provides insights broadly applicable to other emerging markets with similar structural characteristics.

Data, Variable Construction, and Methodology

This section provides an overview of the sample and data sources, describes the construction of key variables, and outlines the methodological framework adopted in this paper.

Sample

To conduct our tests, we obtained data from Kuwait Clearing Company, Thomson Datastream, and Boursa Kuwait. Kuwait Clearing Company data consisted of daily individual and institutional trading volumes for each stock for the period from January 2013 to December 2018. Thomson Datastream data consisted of daily stock-adjusted closing prices, trading volume, shares outstanding, as well as the highest and lowest stock prices of the day for the period from January 2013 to December 2018. Our monthly data included firm size, financial leverage, and market-to-book ratio. Boursa Kuwait data comprised intraday trading data gathered for the period between January 2013 and December 2018.

We chose to use data from the Kuwait Clearing Company due to its comprehensive coverage of all stock trades in Boursa Kuwait. Unlike other datasets, which may only include transactions from select brokerage firms, the Kuwait Clearing Company data provides a complete view of market activity, thereby eliminating any selection bias associated with broker-specific samples. Additionally, the unique setting of Boursa Kuwait, with the absence of market makers until 2019, offers an opportunity to study liquidity dynamics without the influence of designated liquidity providers. This period allows for a clear examination of the impact of individual trading on liquidity without the influence of market makers, who were gradually and unevenly introduced from 2019 onward. Using data from 2019 onward would risk contaminating the clean setting, as the initial introduction of market makers in Kuwait was both fragmented and gradual. This inconsistency means that any post-2018 data would include a mix of trading conditions, even at the stock level, where some stock inventories are held by market makers while others are not.[5] Furthermore, the onset of the COVID-19 pandemic in early 2020 introduced additional market volatility and structural impacts—some of which may have been influenced by monetary policy—on trading behavior and liquidity. This further supports our decision to limit data coverage to 2018, as it enables us to isolate our findings from the unprecedented market disruptions caused by the pandemic.

Variable Construction

This subsection describes the construction of key variables used in the study, the justifications behind their choice, and offers an explanation of their relevance to the research framework.

Individual Trading Intensity

The monthly variable of the individual trading intensity ITIi,t is constructed as follows:

$$ITI_{i,t} = \frac{1}{Days_t^i} \sum_{d=1}^{\text{Days}_t^i} \frac{IDV_d^i}{V_d^i}, \tag{1}$$

where IDV_d^i is the volume of individual trading during day d for stock i and V_d^i is the total trading volume during day d for stock i.

[5] The role of market makers and their differential impact on liquidity is not central to our research question; rather, our focus is on the informed trading behavior of individuals and the liquidity they provide.

Liquidity Proxies

We define liquidity using two proxies. We do not use the bid-ask spread as commonly used in the literature to measure liquidity since Boursa Kuwait is order-driven with a continuous flow of buy and sell orders from market participants, without participation of market makers.[6] The two liquidity proxies we employ are as follows:

(I) A simple monthly average of high-low spread (Leirvik et al., 2017), calculated from daily share price data for stock i in day d:

$$HL_{i,t} = \frac{1}{\text{Days}_t^i} \sum_{d=1}^{\text{Days}_t^i} \frac{H_d^i - L_d^i}{H_d^i}, \tag{2}$$

where H^i_d (L^i_d) is the highest (lowest) price during day d for stock i.

The decision to use the high-low spread as a primary measure of liquidity is driven by its suitability in emerging markets where bid-ask spread data may not be available consistently. Given the lower frequency of quotes and larger price fluctuations typical of Boursa Kuwait, the high-low spread provides a more reliable proxy for the transaction cost faced by traders. This choice allows us to better capture the market's liquidity conditions compared to traditional measures that may be less applicable in this unique context.

(II) The average turnover value of the month calculated from daily defined data for stock i in day d:

$$TOV_{i,t} = \frac{1}{\text{Days}_t^i} \sum_{d=1}^{\text{Days}_t^i} \frac{VL_d^i}{SHO_d^i}, \tag{3}$$

where VL^i_d is the value of daily shares traded and SHO^i_d is the total number of outstanding shares for stock i in day d.

We use Turnover Value (TOV) as another primary measure of liquidity because it captures the trading activity relative to the size of the stock, providing insights into how actively a stock is traded (Amihud & Mendelson, 1986). TOV is particularly suitable for emerging markets where trading volume alone may not fully reflect market conditions due to the presence of large, infrequent transactions. By

[6] Order-driven markets are advantageous in our setting, whereby all traders view the entire order book, thereby increasing transparency and demand-supply informativeness.

considering the value of traded shares rather than the sheer quantity, TOV provides a more comprehensive perspective on liquidity that is sensitive to price changes, offering an effective measure of market depth and trading efficiency.

PIN Proxy

The novel probability of informed trading (PIN) models of Easley and O'Hara (1992) and Easley et al. (1996) denote that on a specific day *d*, the expected buy (B_d) and sell (S_d) number of trades follows this model:

$$L(\otimes | B_d, S_d) = \varrho(1-\delta)e^{-(\mu+\varepsilon_b)}\frac{(\mu+\varepsilon_b)^{B_d}}{B_d!}e^{-\varepsilon_s}\frac{\varepsilon_s^{S_d}}{S_d!} + \varrho\delta e^{-\varepsilon_b}\frac{\varepsilon_b^{B_d}}{B_d!}e^{-(\mu+\varepsilon_s)}\frac{(\mu+\varepsilon_s)^{S_d}}{S_d!} + (1-\varrho)e^{-\varepsilon_b}\frac{\varepsilon_b^{B_d}}{B_d!}e^{-\varepsilon_s}\frac{\varepsilon_s^{S_d}}{S_d!}, \tag{4}$$

where $\otimes$ = (ϱ, δ, μ, ε_b, and ε_s) indicates the parameters for the trading process. Specifically, ϱ indicates the probability that an information event will occur, δ indicates the likelihood of bad news occurrence, and $1 - \delta$ indicates the likelihood of good news occurrence. μ denotes the rate of arrival by informed traders buying good news or selling bad news when an information event occurs. ε_b denotes the rate of arrival by uninformed traders submitting buy orders, while ε_s denotes the rate of arrival by uninformed traders submitting sell orders. These arrival rates have a daily frequency.

Furthermore, the tick rule is used to decide whether the trade is a buy or sell order depending on price movements relative to earlier trades (Lee & Ready, 1991).[7] For example, if the transaction price is higher (lower) than the previous transaction, it is deemed as a buy (sell). Additionally, if the price is unchanged but the previous tick change was up (down), then the trade is marked as a buy (sell).

We define the joint likelihood of observing a sequence of daily buy and sell trades over trading days as:

$$L(\otimes | M) = \prod_{d=1}^{D} L(\otimes | B_d, S_d), \tag{5}$$

where the trading days $d = 1,..., D$ (assuming independent days), and $M = ((B_1, S_1), ..., (B_d, S_d))$ is the dataset. Following the original model of Easley and O'Hara (1992), we define the Probability of Informed Trading (PIN) as:

[7] Our intraday data contain no information about trade direction (buy or sell) or bid-and-ask prices, so we use the tick rule from Lee and Ready (1991) to determine trade direction.

$$\text{PIN} = \frac{\varrho\mu}{\varrho\mu + \varepsilon_b + \varepsilon_s} \tag{6}$$

We estimate a 60-day PIN at the end of each month on a rolling basis following the boundary solutions of Yan and Zhang (2012).[8] The boundary solutions of Yan and Zhang (2012) are considered an improvement over the original PIN model of the estimators of Easley and O'Hara (1992) and Easley et al. (1996). Following Yan and Zhang (2012), the probability parameters ϱ and δ are bounded (between 0 and 1) with equidistant values within the interval as initial values. The arrival rates μ, ε_b, and ε_s are unbounded (from 0 to +∞), with initial values estimated using the moment conditions for the probability distributions of daily buys and sells. The joint probability distributions of *B* and *S* are the same as those in Equation (4), from which we derive the marginal expected values of *B* and *S* as follows:

$$E(B) = \varrho(1-\delta)\mu_{+}\varepsilon_b, \tag{7}$$

$$E(S) = \varrho\delta\mu_{+}\varepsilon_s, \tag{8}$$

Equations (7) and (8) set the initial values for the trading-process parameters. First, we divide the interval [0, 1] equally and choose equidistant values in the interval for ϱ and δ. Then, we replace *E*(*B*) and *E*(*S*) with sample averages *AB* and *AS*. As ϱ (1 − δ) in Equation (7) is always positive and εb is less than *AB*, the initial values of ε_b can be the fractions of *AB*. Then, Equations (7) and (8) are solved simultaneously to generate the initial values of ε_s and μ. As such, the five parameters take the following initial values:

$$\varrho^0 = \varrho_i, \delta^0 = \delta_j, \varepsilon_b^0 = \gamma_k.AB, \mu^0 = \frac{AB - \varepsilon_b^0}{\varrho^0 \cdot (1-\delta^0)}$$

and

$$\varepsilon_s^0 = AS - \varrho^0 \cdot \delta^0 \cdot \mu^0 \tag{9}$$

In Yan and Zhang (2012), the probability parameters ϱ and δ have set values, X = (0.1, 0.3, 0.5, 0.7, 0.9), one at a time. Furthermore, the combinations of ϱ_i, δ_j, and γ_k produce 125 sets of initial values, with a restriction that is unacceptable for the combination, leading to a negative value of ε_s^0.

Following the algorithm of Yan and Zhang (2012) to obtain an estimate of PIN, denoted as YZPIN in the regression tables to distinguish it from other vari-

[8] Following (Easley et al., 2002), the original PIN parameter is estimated over a sample of at least 60 days.

ants of PIN models, the process involves the following three steps: (1) construct the set values of the daily number of buys and sells; (2) run the maximization procedure of Easley et al., (2010) for all sets and record the corresponding solutions; (3) if solutions exist only on the boundary, then we take this as evidence that the optimum should also arise on the boundary, and hence select the boundary solution yielding the maximum value of the objective function as the maximum likelihood estimate (MLE). Otherwise, we eliminate the boundary solutions and select the non-boundary solution with the highest value of the objective function as the MLE.

The Probability of Informed Trading (PIN) is employed as a measure to capture the extent of informed trading in the market. PIN is particularly useful in distinguishing between informed traders, who trade based on private information, and noise traders, whose actions are largely uninformed. This distinction can be significant if and when individual investors dominate and significantly contribute to market volatility. Using PIN allows us to assess the degree to which private information is reflected in stock prices and how it correlates with trading intensity by individual traders. Moreover, the application of PIN is highly relevant in emerging markets like Kuwait, where the asymmetry of information is more pronounced, and understanding the dynamics between informed and uninformed trading can shed light on broader market efficiency issues.

To add more intuition into this measure, PIN helps us understand how much of the trading activity in a market is driven by traders with access to non-public, material information. Essentially, a higher PIN value suggests that informed traders, acting on private insights about a firm's future performance, are playing a significant role in price formation. In contrast, a lower PIN value indicates that most trades are made by uninformed participants, which is often the case with retail investors who tend to react to market sentiment or public news without deep, fundamental insights. In the context of our study, examining the relationship between PIN and individual trading intensity provides valuable information about whether retail traders contribute positively to price discovery or simply add noise, thereby making the market less efficient.

Descriptive Statistics

The summary statistics of our main variables with 262,727 firm-day observations from 173 unique firms are reported in Table 2. Panel (A) of Table 2 reports the mean, median, standard deviation, and different percentile cuts for the entire sample, whereas Panel (B) reports the mean, median, and standard deviation for the upper and lower tertiles of the sample.

Table 2
Summary Statistics

This table reports the summary statistics covering the time-period between January 2013 and December 2018 with 262,727 firm-day observations from 173 unique firms. $ITI_{i,t}$ is stock *i*'s monthly average of individual trading intensity, $R_{i,t}$ is stock *i*'s monthly average returns, $HL_{i,t}$ is stock *i*'s monthly average high-low liquidity estimator, $TOV_{i,t}$ is stock *i*'s monthly average turnover value, $LMC_{i,t}$ is the monthly log of the firm's market capitalization, $OOP_{i,t}$ is stock *i*'s monthly average one over price ratio, $FFS_{i,t}$ is stock *i*'s monthly average free float to total shares outstanding ratio, $YZPIN_{i,t}$ is stock *i*'s 60-day rolling PIN at the end of each month *t* estimated following (Yan & Zhang, 2012), and $GANPIN_{i,t}$ is stock *i*'s 60-day rolling PIN at the end of each month t estimated following (Gan et al., 2015). Panel (A) reports the statistics for the entire sample, whereas Panel (B) reports the statistics for the top and bottom tertiles of the sample (top and bottom 33 percentiles of $ITI_{i,t}$).

Panel (A) - Full Sample

	Mean	Median	SD	P1	P25	P75	P99
$ITI_{i,t}$	0.63	0.66	0.21	0.06	0.50	0.77	1.00
$R_{i,t}$	0.00	-0.00	0.16	-0.26	-0.05	0.03	0.45
$HL_{i,t}$	0.03	0.02	0.03	0.00	0.01	0.03	0.11
$TOV_{i,t}$	0.35	0.06	1.50	0.00	0.02	0.24	4.53
$LMC_{i,t}$	3.67	3.39	1.46	1.10	2.64	4.44	8.03
$OOP_{i,t}$	0.01	0.01	0.01	0.00	0.00	0.02	0.05
$FFS_{i,t}$	0.29	0.15	0.58	0.01	0.07	0.34	2.40
$YZPIN_{i,t}$	0.16	0.15	0.09	0.02	0.11	0.21	0.44
$GANPIN_{i,t}$	0.21	0.20	0.09	0.05	0.15	0.25	0.53

Panel (B) - Top and Bottom Tertiles

	Top Tertile			Bottom Tertile		
	Mean	**Median**	**SD**	**Mean**	**Median**	**SD**
$ITI_{i,t}$	0.385	0.415	0.136	0.836	0.819	0.075
$R_{i,t}$	0.005	-0.000	0.097	0.004	-0.012	0.166
$HL_{i,t}$	0.018	0.015	0.016	0.030	0.028	0.021
$TOV_{i,t}$	0.362	0.095	1.450	0.296	0.050	0.925
$LMC_{i,t}$	4.812	4.643	1.582	2.962	2.982	0.919
$OOP_{i,t}$	0.006	0.003	0.006	0.016	0.014	0.011
$FFS_{i,t}$	0.220	0.100	0.525	0.373	0.207	0.706
$YZPIN_{i,t}$	0.175	0.146	0.109	0.161	0.150	0.069
$GANPIN_{i,t}$	0.221	0.192	0.127	0.208	0.203	0.072

By highlighting the distribution of individual trading intensity $ITI_{i,t}$ across all stocks, Table 2 notably shows that when stocks are in the highest $ITI_{i,t}$ tertile have a significantly larger high-low spread compared to those in the lowest tertile, suggesting that higher $ITI_{i,t\ i}$s associated with poorer liquidity. This is consistent with the hypothesis that individual traders, often considered noise traders, may contribute to less efficient price formation.

Table 3 reports the *t*-test statistics for our main outcome variables. The results of the *t*-test suggest that the stocks in the top tertile (upper 33 percentiles) of $ITI_{i,t}$ have statistically significant lower average liquidity in terms of $HL_{i,t}$ and $TOV_{i,t}$, and statistically significant lower average probability of informed trading ($YZPIN_{i,t}$) and ($GANPIN_{i,t}$), compared to the stocks in the bottom tertile (lower 33 percentiles) of $ITI_{i,t}$.

Table 3
Mean Equality Test

This table reports the mean equality test for our main outcome variables for the period of January 2013 to December 2018. Top-tertile mean represents the mean of the top group (top 33 percentiles) of $ITI_{i,t}$, whereas Bottom-tertile mean represents the mean of the bottom group (bottom 33 percentiles) of $ITI_{i,t}$. $ITI_{i,t}$ is stock i's monthly average individual trading intensity, $R_{i,t}$ is stock i's monthly average returns, $HL_{i,t}$ is stock i's monthly average high-low liquidity estimator, $TOV_{i,t}$ is stock i's monthly average turnover value, $YZPIN_{i,t}$ is stock i's 60-day rolling PIN at the end of each month t estimated following (Yan & Zhang, 2012), and $GANPIN_{i,t}$ is stock i's 60-day rolling PIN at the end of each month t estimated following (Gan et al., 2015). The p-values of the mean equality test correspond to the t-test.

	Top-Tertile Mean	Bottom-Tertile Mean	Δ Mean	*t*-stat	*p*-value
$R_{i,t}$	0.004	0.005	0.001	0.355	0.723
$HL_{i,t}$	0.030	0.018	-0.012	-24.724	< 0.001
$TOV_{i,t}$	0.296	0.362	0.066	2.096	0.036
$YZPIN_{i,t}$	0.161	0.175	0.014	3.466	< 0.001
$GANPIN_{i,t}$	0.208	0.221	0.013	2.895	0.004

Empirical Tests

This subsection describes the methodology, empirical approach, and tests used to examine the study's hypotheses, focusing on relationships between the study's key variables, and providing a basis for the empirical findings presented later.

Returns, Liquidity, and ITI

Panel data regressions minimize estimation bias and problems associated with multicollinearity, and considers individual heterogeneity as well as time-varying relations between outcome and control variables (Baltagi, 2008; Hsiao, 2014). Thus, to examine the interaction between individual trading intensity and stock returns and liquidity, we apply a panel test, controlling for firm-specific characteristics, and estimate our model as follows:

$$R_{i,t+1} = \alpha_0 + \alpha_1 ITI_{i,t} + \beta X_{i,t} + \varepsilon_{i,t}, \tag{10}$$

where $R_{i,t+1}$ is the monthly average return of stock i regressed on the lagged values of the $ITI_{i,t}$ and the vector of firm-specific characteristics $X_{i,t}$, and ε_t is the error term.

$X_{i,t}$ includes the previously defined firm-specific variables, the monthly log of market capitalization $LMC_{i,t}$, the monthly average of one-over-price ratio $OOP_{i,t}$, and the monthly average of free float shares $FFS_{i,t}$.[9]

Informed Trading and ITI

To examine the interaction between individual trading intensity (*ITI*) and the probability of informed trading (*YZPIN*), we apply a panel test based on the following model:

$$YZPIN_{i,t+1} = \alpha_0 + \alpha_1 ITI_{i,t} + \beta X_{i,t} + \varepsilon_{i,t}, \tag{11}$$

where $YZPIN_{i,t+1}$ is the 60-day PIN at the end of each month (on a rolling basis) of stock *i* regressed on the lagged values of the $ITI_{i,t}$ and the vector of firm-specific characteristics $X_{i,t}$, and ε_t is the error term. $X_{i,t}$ includes the previously defined firm-specific variables, the monthly log of market capitalization $LMC_{i,t}$, the monthly average of one-over-price ratio $OOP_{i,t}$, and the monthly average of free float shares $FFS_{i,t}$.

Other Firm Specific Variables

Our primary regression models, specified in Equations (10) and (11), employ market-based independent variables aggregated at the firm-month level to examine the effects of individual trading intensity on stock liquidity and the probability of informed trading. However, prior literature highlights that firm-specific accounting-based variables can play a significant role in explaining liquidity and informed trading outcomes. To account for this, we repeat our tests while controlling for variables measured quarterly at the firm level, which have been identified in the literature as key determinants of liquidity and informed trading.

For example, we include firm size proxied by the natural logarithm of total assets *(Log(TA))*, as larger firms tend to exhibit a higher trading activity coupled with narrower bid-ask spreads due to better information dissemination and reduced trading frictions (Amihud, 2002; Rindi, 2008). Financial leverage (*Leverage*), calculated as the ratio of total debt to total assets, is incorporated as it reflects a firm's financial risk. Higher leverage has been associated with increased uncertainty and lower liquidity due to the elevated risk of default (Ali et al., 2016). Finally, profitability, proxied by return on assets (ROA), is included to capture a firm's operational

[9] We attempt to reduce the effects of outliers in the sample by taking the natural logarithm of the firm's market capitalization (Galema et al., 2008; Hong & Kacperczyk, 2009).

efficiency and performance. More profitable firms are often viewed as less risky, which can attract informed trading and improve liquidity (Easley et al., 2002).

These additional dimensions of firm-specific characteristics may confound the relationship between individual trading intensity, stock liquidity, and informed trading. Hence, their inclusion ensures a more comprehensive analysis of the factors influencing market outcomes in our empirical setting.

Self-Selection

We recognize the potential concern of selection bias that could affect the validity of our results. For instance, Graham and Kumar (2006) find that retail investors self-select into dividend-paying stocks based on personal tax and income preferences. In our case, individual investors might preferentially choose to trade illiquid stocks due to some unobservable factors that are not captured in our dataset. To mitigate this concern, we employ a two-stage self-selection model following Heckman (1979) to determine whether selection based on unobserved factors significantly impacts our main findings.

$$Y_{i(t+1)} = \beta X_{it} + \sigma T_{it} + \epsilon, \text{ where } T_{it} = \begin{cases} 1, & \text{if } T_{it}^{*} > 0, \\ 0, & \text{otherwise.} \end{cases}$$

$$T_{it}^{*} = \delta Z_{it} + \mu, \tag{12}$$

$$Prob(T_{it} = 1 \mid Z_{it}) = \Phi(\delta Z_{it})$$

$$\lambda_{T_i=1} = \frac{\phi(\delta Z_{it})}{\Phi(\delta Z_{it})}, \ \lambda_{T_i=0} = \frac{-\phi(\delta Z_{it})}{1 - \Phi(\delta Z_{it})}.$$

In this set of Equations, $Y_{i(t+1)}$ represents the outcome variable of interest which is either liquidity or PIN. X_{it} is the set of explanatory factors used in the second stage to predict the outcome of interest. T_{it} is the treatment variable, which is a binary variable indicating whether a stock experiences high individual trading intensity ($T_{it} = 1$) or not ($T_{it} = 0$), which serves as the selection mechanism and is modeled in the first stage. Z_{it} is the set of explanatory factors used in the first stage to model the probability of high individual trading intensity. Prob ($T_{it} =1|Z_{it}$) represents the probability that a stock experiences high individual trading intensity ($T_{it} = 1$) given the instrumental variables (Z_{it}) used in the first stage of the Heckman model. It is modeled using a probit regression, where the probability function is the cumulative distribution function of the standard normal distribution. This probability captures the likelihood of the treatment (high individual trading intensity) occurring based on observable characteristics, such as stock volatility, market capitalization, or turnover ratio. These variables serve as predictors in the selection equation to determine the incidence of high individual trading intensity. Finally, λ is the inverse mills ratio, derived from the first stage of the Heckman model. This term is then included in the second stage to correct for potential selection bias. It accounts for unobservable factors influencing both the likelihood of high individual trading intensity and the stock liquidity outcome.

The choice to use a Heckman selection model is motivated by the potential selection bias related to the types of stocks that individual investors choose to trade. Our primary concern is not with the censoring of the dependent variable, but rather with unobserved factors that could influence an individual trader's decision to engage with specific stocks. Individual investors may preferentially select stocks based on unobservable characteristics, such as perceived future performance or risk preferences, which are not captured directly in our dataset. If these unobserved factors are correlated with our outcome variables (e.g., liquidity measures or the probability of informed trading), failing to account for them could introduce bias into our regression estimates. The Heckman model allows us to correct for this potential bias by modeling the selection process explicitly. In the first stage, we estimate the probability that a stock is heavily traded by individuals, using observable characteristics. By including the inverse Mills ratio in the second stage, we control for any selection on unobservables, ensuring that our estimates of liquidity and informed trading are not biased due to the non-random selection of stocks by individual investors.

In the first stage of the Heckman procedure, we run a probit regression where the dependent variable is a binary indicator set to 1 if the individual trading intensity ($ITI_{i,t}$) for a stock is greater than or equal to 0.5, indicating that the stock is heavily traded by individual investors. This segmentation allows us to categorize stocks into two distinct groups: those that are heavily traded by individuals and those that are not. The independent variables used in this first stage regression include observable characteristics that are expected to influence the likelihood of a stock being heavily traded by individuals. Specifically, we include the stock's historical returns, the size of the firm, the monthly average of the one-over-price ratio, and the monthly average of free-float shares. These variables are carefully chosen as they capture important aspects of a stock's attractiveness to individual investors, such as liquidity, affordability, and availability. The results of this probit regression help us understand the determinants of individual investor preferences and allow us to estimate the probability that a stock is selected by individual traders, conditional on all observable covariates.

After estimating the probit model in the first stage, we compute the inverse Mills ratio, which is then included in the second stage regression. In this second stage, our dependent variable is one of our key outcome measures, either a liquidity proxy or the probability of informed trading (PIN). By including the inverse Mills ratio in the second stage, we control for any potential selection bias stemming from unobservable factors that might influence both the choice of stock by individual investors and the outcomes we are studying. Essentially, this approach helps correct for any omitted variable bias that would otherwise distort our results.

Empirical Results

This section presents the main findings of our paper, linking the results to the research objectives, hypothesis, and providing insights into the impact of individual trading on key outcomes.

Returns, Liquidity, and ITI

Table 4 shows the results of stock market returns ($R_{i,t+1}$) and the individual trading intensity ($ITI_{i,t}$) regression, controlling for known determinants that affect stock returns. The results suggest that the relationship between stock market returns ($R_{i,t+1}$) and individual trading intensity ($ITI_{i,t}$) is negative and statistically significant. Interpreting the results in the most saturated regression specification in column (5), we find that a one percentage point increase in individual trading intensity is associated with 2.6 basis points decrease in average monthly returns (on a monthly basis) for the stock. This finding implies that higher levels of individual trading are correlated with lower future returns, potentially due to the uninformed nature of these trades. This result aligns with prior literature suggesting that increased noise trading by individuals can lead to price distortions and ultimately reduce average returns (e.g., Barber & Odean, 2000; Kaniel et al., 2008; KR & Fu, 2014).

Table 4
Returns and Individual Trading Intensity

This table reports OLS regression results where the effects of individual trading intensity on monthly returns are shown throughout the time-period between January 2013 and December 2018. $ITI_{i,t}$ is stock i's monthly average individual trading intensity, $LMC_{i,t}$ is the monthly log of the firm's market capitalization, $OOP_{i,t}$ is stock i's monthly average one over price ratio, $FFS_{i,t}$ is stock i's monthly average free float to total shares outstanding ratio. For all columns, robust t-statistics are reported in parentheses, and the regression specification in column (5) is robust double clustered on firm and year-month levels.

	$\mathbf{R}_{i(t+1)}$				
	(1)	**(2)**	**(3)**	**(4)**	**(5)**
$ITI_{i,t}$	-0.0240*	-0.0231	-0.0260*	-0.0258+	-0.0258+
	(-1.99)	(-1.57)	(-2.25)	(-1.85)	(-2.00)
$LMC_{i,t}$	-0.0008	-0.0004	-0.0015	-0.0013	-0.0013
	(-0.20)	(-0.07)	(-0.35)	(-0.21)	(-0.23)
$OOP_{i,t}$	0.9594	1.1195	0.8068	0.9436	0.9436
	(1.39)	(1.30)	(1.05)	(0.97)	(0.99)
$FFS_{i,t}$	0.0034	0.0037	0.0026	0.0028	0.0028
	(0.75)	(0.71)	(0.58)	(0.52)	(0.47)
Obs.	8,883	8,883	8,883	8,883	8,883
R^2	0.003	0.004	0.078	0.078	0.078
Sector FE	NO	YES	NO	YES	YES
Year-Month FE	NO	NO	YES	YES	YES
Standard Errors	Robust	Robust	Robust	Robust	Double Clustering

** $p < 0.01$, * $p < 0.05$, + $p < 0.10$

The same tests are repeated with liquidity proxies as the dependent variable in Tables 5 and 6. The results suggest that the relationship between $ITI_{i,t}$ and the two liquidity proxies ($HL_{i,t+1}$ and $TOV_{i,t+1}$) are consistent and statistically significant, indicating that individuals trading intensity is negatively associated with the stock's liquidity. We find a similar result when we repeat our regression tests, including sector fixed effects, year-month fixed effects, and double clustering standard errors on year-month and firm dimensions. Specifically, when interpreting the results in the most saturated regression specification in column (5) of the said tables, we find that a one percentage point increase in individual trading intensity is associated with 4.8 basis points increase in *HL* spread, and a 0.44 percentage point decrease in the stock's monthly turnover value. These findings support our hypothesis regarding the negative relationship between individual trading intensity and stock liquidity, and align with the work of Barber and Odean (2000), who characterize individual investors as noise traders, and highlight how noise trading demands liquidity and increases price distortions, which is consistent with our observations in the context of the Kuwaiti market.

Table 5
High-Low Liquidity Spread and Individual Trading Intensity

This table reports OLS regression results of the effects of individual trading intensity on monthly average high-low spread $HL_{i,t}$, covering the time-period between January 2013 and December 2018. $ITI_{i,t}$ is stock *i*'s monthly average individual trading intensity, $LMC_{i,t}$ is the monthly log of the firm's market capitalization, $OOP_{i,t}$ is stock *i*'s monthly average one over price ratio, $FFS_{i,t}$ is stock *i*'s monthly average free float to total shares outstanding ratio. For all columns, robust *t*-statistics are reported in parentheses, and the regression specification in column (5) is robust double clustered on firm and year- month levels.

	$HL_{i(t+1)}$				
	(1)	(2)	(3)	(4)	(5)
$ITI_{i,t}$	0.0067**	0.0056**	0.0059**	0.0048**	0.0048+
	(3.80)	(2.96)	(3.38)	(2.59)	(1.92)
$LMC_{i,t}$	-0.0009**	-0.0010**	-0.0009**	-0.0011**	-0.0011+
	(-3.34)	(-2.68)	(-3.35)	(-2.86)	(-1.70)
$OOP_{i,t}$	0.5359**	0.5024**	0.5774**	0.5476**	0.5476**
	(16.65)	(13.30)	(17.02)	(13.80)	(7.77)
$FFS_{i,t}$	0.0028**	0.0026**	0.0027**	0.0025**	0.0025**
	(4.99)	(4.52)	(5.01)	(4.52)	(4.88)
Obs.	8,883	8,883	8,883	8,883	8,883
R^2	0.141	0.149	0.219	0.227	0.227
Sector FE	NO	YES	NO	YES	YES
Year-Month FE	NO	NO	YES	YES	YES
Standard Errors	Robust	Robust	Robust	Robust	Double Clustering

** $p < 0.01$, * $p < 0.05$, + $p < 0.10$

Table 6
The Turnover Value and Individual Trading Intensity

This table reports OLS regression results of the effects of individual trading intensity on the monthly average value turnover $TOV_{i,t}$, covering the time-period between January 2013 and December 2018. $ITI_{i,t}$ is stock *i*'s monthly average individual trading intensity, $LMC_{i,t}$ is the monthly log of the firm's market capitalization, $OOP_{i,t}$ is stock *i*'s monthly average one over price ratio, $FFS_{i,t}$ is stock *i*'s monthly average free float to total shares outstanding ratio. For all columns, robust *t*-statistics are reported in parentheses, and the regression specification in column (5) is robust double clustered on firm and year-month levels.

	$TOV_{i(t+1)}$				
	(1)	(2)	(3)	(4)	(5)
$ITI_{i,t}$	-0.3004*	-0.3054*	-0.4333**	-0.4356**	-0.4356*
	(-2.34)	(-2.49)	(-3.39)	(-3.54)	(-2.64)
$LMC_{i,t}$	-0.0203	-0.0280	-0.0135	-0.0246	-0.0246
	(-0.77)	(-1.20)	(-0.51)	(-1.06)	(-0.46)
$OOP_{i,t}$	-4.9784**	-6.3478**	1.7179	1.2954	1.2954
	(-2.64)	(-3.14)	(0.85)	(0.61)	(0.27)
$FFS_{i,t}$	0.1495**	0.1491**	0.1573**	0.1569**	0.1569*
	(4.14)	(4.27)	(4.33)	(4.48)	(2.09)
Obs.	8,883	8,883	8,883	8,883	8,883
R^2	0.010	0.016	0.079	0.085	0.085
Sector FE	NO	YES	NO	YES	YES
Year-Month FE	NO	NO	YES	YES	YES
Standard Errors	Robust	Robust	Robust	Robust	Double Clustering

** $p < 0.01$, * $p < 0.05$, + $p < 0.10$

Informed Trading and ITI

Table 7 shows the results of *YZPIN* and individual trading intensity ($ITI_{i,t}$) regression including all control variables. The results suggest that the relationship between $YZPIN_{i,t+1}$ and $ITI_{i,t}$ is negative and statistically significant. Specifically, when interpreting the results in the most saturated regression specification in column (5), we find that a one percentage point increase in individual trading intensity is associated with a 0.05 percentage point decrease in the probability of informed trading as proxied by *YZPIN*, which indicates that stocks with higher percentages of individual trading intensity are associated with a lower probability of informed trading. The specification in column (6) repeats the analysis using tobit regressions as a robustness check, given the censored nature of the PIN measure which is bound between 0 and 1.

Table 7
YZPIN and Individual Trading Intensity

This table reports regression results of the effects of individual trading intensity on *YZPIN*, covering the time-period between January 2013 and December 2018. The dependent variable $YZPIN_{i,t}$ is stock i's 60-day rolling PIN at the end of each month t estimated following (Yan & Zhang, 2012). $ITI_{i,t}$ is stock i's monthly average individual trading intensity, $LMC_{i,t}$ is the monthly log of the firm's market capitalization, $OOP_{i,t}$ is stock i's monthly average one over price ratio, $FFS_{i,t}$ is stock i's monthly average free float to total shares outstanding ratio. For all columns, robust t-statistics are reported in parentheses, and the regression specification in column (5) is robust double clustered on firm and year-month levels.

	$\mathbf{YZPIN}_{i(t+1)}$					
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
$ITI_{i,t}$	-0.0310*	-0.0473**	-0.0292*	-0.0489**	-0.0489*	-0.0489**
	(-2.37)	(-3.49)	(-2.23)	(-3.59)	(-2.28)	(-3.63)
$LMC_{i,t}$	-0.0039+	-0.0105**	-0.0034	-0.0100**	-0.0100+	-0.0100**
	(-1.76)	(-3.89)	(-1.51)	(-3.73)	(-1.88)	(-3.77)
$OOP_{i,t}$	-0.9411**	-0.9944**	-0.8987**	-0.8443**	-0.8443**	-0.8443**
	(-5.02)	(-5.13)	(-4.08)	(-3.77)	(-2.69)	(-3.81)
$FFS_{i,t}$	-0.0067	-0.0122	-0.0075	-0.0136+	-0.0136	-0.0136+
	(-0.89)	(-1.53)	(-1.02)	(-1.71)	(-1.00)	(-1.73)
Obs.	3,055	3,055	3,055	3,055	3,055	3,055
R^2	0.014	0.033	0.057	0.076	0.076	
Sector FE	NO	YES	NO	YES	YES	NO
Year-Month FE	NO	NO	YES	YES	YES	NO
Standard Errors	Robust	Robust	Robust	Robust	Double Clustering	Robust
Regression Type	OLS	OLS	OLS	OLS	OLS	Tobit

** $p < 0.01$, * $p < 0.05$, + $p < 0.10$

The negative relationship between $ITI_{i,t}$ and informed trading proxies, such as the *YZPIN* metric, suggests that individual traders are less informed relative to institutional investors. This is evident from the consistent decrease in the probability of informed trading as $ITI_{i,t}$ increases, indicating that greater individual involvement dilutes the quality of information embedded in prices. This supports our second hypothesis. This finding corroborates Rindi (2008), who emphasizes the adverse impact of uninformed trading on market liquidity. This result has implications for policymakers, as promoting institutional participation may enhance market efficiency.

Robustness Checks

This subsection validates the findings through additional tests, alternative specifications, and firm-level measures.

GANPIN

As a robustness check, we address the boundary solution problem associated with the original estimation of the Probability of Informed Trading (PIN). To do so, we follow the approach outlined by (Gan et al., 2015), which employs cluster analysis to enhance the estimation process. This method is designed to overcome the limitations of traditional maximum likelihood estimation (MLE), particularly in cases where the MLE may converge to unrealistic boundary values. By using cluster analysis, we are able to obtain more reliable and stable estimates of the PIN, ensuring that our results are not driven by estimation issues inherent in the MLE approach

Table 8 shows the results of the regression using *GANPIN* following Gan et al. (2015), and we find that the results are in line with what we found earlier, suggesting that the relationship between individual trading intensity and the probability of informed trading is negative and statistically significant. Specifically, when interpreting the results in the most saturated regression specification in column (5), we find that a one percentage point increase in individual trading intensity is associated with a 0.08 percentage point decrease in the probability of informed trading as proxied by *GANPIN*, which indicates that stocks with higher percentages of individual trading intensity are associated with a lower probability of informed trading. The specification in column (6) repeats the analysis using tobit regressions as a robustness check, given the censored nature of the PIN measure which is bound between 0 and 1.

Table 8
GANPIN and Individual Trading Intensity

This table reports regression results of the effects of individual trading intensity on *GANPIN*, covering the time-period between January 2013 and December 2018. The dependent variable $GANPIN_{i,t}$ is stock i's 60-day rolling PIN at the end of each month *t* estimated following (Gan et al., 2015). $ITI_{i,t}$ is stock *i*'s monthly average individual trading intensity, $LMC_{i,t}$ is the monthly log of the firm's market capitalization, $OOP_{i,t}$ is stock *i*'s monthly average one over price ratio, $FFS_{i,t}$ is stock *i*'s monthly average free float to total shares outstanding ratio. For all columns, robust *t*-statistics are reported in parentheses, and the regression specification in column (5) is robust double clustered on firm and year-month levels.

	$GANPIN_{i(t+1)}$					
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
$ITI_{i,t}$	-0.0845**	-0.0915**	-0.0721**	-0.0790**	-0.0790**	-0.0791**
	(-5.49)	(-5.88)	(-4.71)	(-5.12)	(-3.30)	(-5.18)
$LMC_{i,t}$	-0.0153**	-0.0176**	-0.0159**	-0.0176**	-0.0176**	-0.0177**
	(-6.30)	(-6.05)	(-6.47)	(-6.08)	(-2.68)	(-6.16)
$OOP_{i,t}$	-1.4114**	-1.3330**	-1.8287**	-1.7560**	-1.7560**	-1.7626**
	(-7.04)	(-6.42)	(-7.71)	(-7.32)	(-3.97)	(-7.40)
$FFS_{i,t}$	-0.0259**	-0.0268**	-0.0277**	-0.0278**	-0.0278+	-0.0280**
	(-3.15)	(-3.05)	(-3.47)	(-3.26)	(-1.73)	(-3.31)
Obs.	3,055	3,055	3,055	3,055	3,055	3,055
R^2	0.024	0.032	0.065	0.071	0.071	
Sector FE	NO	YES	NO	YES	YES	NO
Year-Month FE	NO	NO	YES	YES	YES	NO
Standard Errors	Robust	Robust	Robust	Robust	Robust	Robust
Regression Type	OLS	OLS	OLS	OLS	OLS	Tobit

** $p < 0.01$, * $p < 0.05$, + $p < 0.10$

The robustness of our findings across different measures suggests that the negative relationship between $ITI_{i,t}$ and informed trading is not sensitive to the choice of metric. This consistency strengthens our argument that individual traders are generally uninformed.

Other Firm Specific Variables

The regression results presented in Table 9 suggest that these, now quarterly, firm-level characteristics are indeed influential in explaining some of the variation in liquidity and informed trading, while still controlling for individual trading intensity ($ITI_{i,q}$). Notably, the coefficient for $Log(TA)_{i,q}$ is consistently negative across the models, indicating that larger firms tend to exhibit better liquidity and lower probability of informed trading. This aligns with the notion that larger firms have greater information transparency and lower adverse selection costs, which subsequently improves liquidity (Ali et al., 2016). The negative coefficient of firm size for the liquidity proxies ($HL_{i,q}$ and $TOV_{i,q}$) reaffirms the same notion.

Table 9

Other Firm Specific Variables

This table reports regression results of the effects of individual trading intensity on our main variables controlling for quarterly firm specific determinants, covering the time-period between January 2013 and December 2018. The dependent variables are: Ri,q which is stock i's quarterly average return, $HL_{i,q}$ which is stock *i*'s quarterly average high-low liquidity estimator, $TOV_{i,q}$ which is stock *i*'s quarterly average turnover value, $YZPIN_{i,q}$ which is stock *i*'s 60-day rolling PIN at the end of each quarter q estimated following (Yan & Zhang, 2012), and finally $GANPIN_{i,t}$ which is stock *i*'s 60-day rolling PIN at the end of each quarter q estimated following (Gan et al., 2015). The independent variables are: $ITI_{i,q}$ which is stock *i*'s quarterly average individual trading intensity, $Log(TA)_{i,q}$ which is the quarterly log of the firm i's total asset, Leveragei,q which is stock i's quarterly leverage ratio, $ROA_{i,q}$ which is stock *i*'s quarterly return on assets. The regression specifications in all columns have robust *t*-statistics that are double clustered on firm and year-quarter levels.

	$R_{i(q+1)}$	$HL_{i(q+1)}$	$TOV_{i(q+1)}$	$GANPIN_{i(q+1)}$	$YZPIN_{i(q+1)}$
	(1)	(2)	(3)	(4)	(5)
$ITI_{i,q}$	0.0054	0.0159**	-0.6449+	-0.0694**	-0.0424+
	(0.12)	(5.16)	(-2.02)	(-3.01)	(-1.88)
$Log(TA)_{i,q}$	-0.0091	-0.0025**	-0.0865**	-0.0081+	-0.0053
	(-0.94)	(-4.14)	(-2.92)	(-1.84)	(-1.43)
$Leverage_{i,q}$	0.0008	0.0011*	0.0205	0.0033+	0.0020*
	(0.53)	(2.73)	(1.32)	(2.02)	(2.12)
$ROA_{i,q}$	0.0023**	-0.0003**	-0.0012	0.0004	0.0003
	(2.98)	(-3.74)	(-0.24)	(1.70)	(1.28)

Cont. Other Firm Specific Variables

	$R_{i(q+1)}$	$HL_{i(q+1)}$	$TOV_{i(q+1)}$	$GANPIN_{i(q+1)}$	$YZPIN_{i(q+1)}$
	(1)	(2)	(3)	(4)	(5)
Obs.	3,078	3,078	3,078	1,348	1,348
R^2	0.098	0.216	0.070	0.075	0.091
Sector FE	YES	YES	YES	YES	YES
Year-Quarter FE	YES	YES	YES	YES	YES
Standard Errors	Double Clustering	Double Clustering	Double Clus-tering	Double Clus-tering	Double Clus-tering
Regression Type	OLS	OLS	OLS	OLS	OLS

** $p < 0.01$, * $p < 0.05$, + $p < 0.10$

Leverage, on the other hand, shows mixed effects on different aspects of liquidity and informed trading. In Table 10, the leverage ratio ($Leverage_{i,q}$) has a positive and significant impact on both the high-low liquidity spread ($HL_{i,q}$) and the probability of informed trading as captured by $GANPIN_{i,q}$ and $YZPIN_{i,q.}$ This finding suggests that highly leveraged firms are perceived to carry greater financial risk, potentially increasing the adverse selection cost for traders, thereby reducing stock liquidity and increasing the likelihood of informed trading. This result is consistent with Ali et al. (2016), who emphasize that leverage amplifies financial fragility and can contribute to higher levels of information asymmetry in the market. Additionally, while $ROA_{i,q}$ is positively and significantly associated with returns ($R_{i,q}$) in Table 10, its impact on liquidity proxies and informed trading is less conclusive. The negative relationship between profitability and high-low spread aligns with the understanding that higher profitability improves a firm's stability, attracting more liquidity providers and thereby reducing trading costs.

That said, the negative impact of individual trading intensity remains evident even among these firms, suggesting that uninformed trading can impair liquidity despite solid financial performance. This finding further affirms our hypothesis that individual trading intensity adversely affects both liquidity and the probability of informed trading across different firm characteristics. The observed differential impacts of firm size, leverage, and profitability underscore the importance of firm-specific factors in shaping market dynamics, emphasizing that higher individual trading activity consistently leads to unfavorable liquidity outcomes, as found earlier.

Self-Selection

We validate the robustness of our findings and address selection bias concerns by employing a Heckman (1979) two-stage selection model. This allows us to account for the non-random selection of stocks heavily traded by individuals, ensuring that our conclusions are not influenced by unobserved factors. The results from the first stage regression, as shown in Panel (A) of Table 10, are reassuring: all the observable variables returns, firm size, the monthly average of the one-over-price ratio and the monthly average of free float shares are statistically significant predictors of whether a stock is heavily traded by individuals. This confirms that our model effectively captures the observable factors driving selection.

Table 10
Two-Stage Heckman Selection Regressions

This table reports the results from the Heckman two stage regression to deal with selection due to unobservables. Panel (A) shows the results of the first stage, where the dependent variable is a dummy variable that is equal to 1 if the individual trading intensity for the stock is greater than or equal to 0.5, which segments the stocks into groups of heavily traded by individuals and non-heavily traded by individuals. Panel (B) shows the results of the second stage, where we control for selection due to unobservables via the inverse mills ratio λ generated in the first stage.

Panel (A) - First Stage

	(1)
$R_{i,t}$	0.2113 (1.59)
$LMC_{i,t}$	-0.3932** (-25.06)
$OOP_{i,t}$	37.9700** (10.80)
$FFS_{i,t}$	-0.1705** (-6.78)
Obs.	11,209
R^2	0.253
Sector FE	NO
Year-Month FE	NO
Standard Errors	Robust
Regression Type	Probit

Panel (B) - Second Stage

	$HL_{i(t+1)}$	$TOV_{i(t+1)}$	$GANPIN_{i(t+1)}$	$YZPIN_{i(t+1)}$
	(1)	(2)	(3)	(4)
$ITI_{i,t}$	0.0051+	-0.3335*	-0.0849**	-0.0480*
	(1.96)	(-2.53)	(-3.24)	(-2.04)
$LMC_{i,t}$	-0.0019	-0.1635	-0.0044	-0.0121
	(-1.30)	(-1.63)	(-0.46)	(-1.58)
$OOP_{i,t}$	0.5525**	2.6986	-1.7563**	-0.8443**
	(8.32)	(0.50)	(-4.08)	(-2.68)
$FFS_{i,t}$	0.0020*	0.0822	-0.0083	-0.0167
	(2.47)	(1.23)	(-0.49)	(-1.31)
$\lambda_{i,t}$	0.0039	0.7135	-0.0539	0.0085
	(0.69)	(1.25)	(-1.06)	(0.21)
Obs.	8,867	8,867	3,055	3,055
R^2	0.228	0.088	0.073	0.076
SectorFE	YES	YES	YES	YES
Year-Quarter FE	YES	YES	YES	YES
Standard Errors	Double Clustering	Double Clustering	Double Clustering	Double Clustering
Regression Type	OLS	OLS	OLS	OLS

** $p < 0.01$, * $p < 0.05$, + $p < 0.10$

Moving on to the second stage regression results, as shown in Panel (B) of Table 10, the inverse Mills ratio is found to be statistically insignificant across all specifications. This finding suggests that unobserved factors are not significantly influencing our outcomes, which means that the selection bias based on unobservables is unlikely to be a concern in our analysis. Furthermore, correcting for potential selection bias using the Heckman approach not only reassures us of the robustness of our findings, but also shows that our self-selection corrected results are generally stronger, both in terms of economic magnitude and statistical significance. This provides additional confidence that our primary conclusions are reliable and not driven by selection issues, ultimately reinforcing the validity of our analysis.

Conclusion

Individual traders are crucial participants in financial markets, and their trading behavior has significant implications for market efficiency, particularly in terms of liquidity and price discovery. In this paper, we investigate whether individual traders contribute positively to stock market liquidity and assess the extent to which they can be considered informed traders.

Existing research has presented mixed evidence on the impact of individual trading intensity on stock liquidity. To address this, we utilized a clear and unique empirical setting from Boursa Kuwait, characterized by the absence of market makers until 2019. This allowed us to isolate the effects of individual trading intensity on stock liquidity and the probability of informed trading without the confounding influence of market makers. Our results indicate that higher individual trading intensity is associated with lower stock returns, diminished liquidity, and a lower probability of informed trading. These findings are consistent with theories that classify individual traders as noise traders whose actions contribute to price distortions and increase information asymmetry in the market. Our findings not only validate aspects of existing theories but also introduce new perspectives on the dynamics of individual trader influence, thereby extending the relevance of these frameworks to markets with similar structural characteristics. In other words, by precisely observing the effects of individual trading on liquidity without confounding influences, in the unique setting of an emerging market without the influence of market makers and large individual trading intensity, we slightly push the boundaries of existing theories about noise traders by gaining a clearer understanding of the effects of informed trading, individual traders, on market liquidity. This setting provides a valuable opportunity to understand these market dynamics in a less-intermediated environment.

Our analysis demonstrates that individual trading intensity negatively impacts both stock returns and liquidity, with uninformed trading behavior being a likely driver of these outcomes. The unique characteristics of Boursa Kuwait, with its high proportion of individual traders and the absence of market makers during the study period, provide valuable insights into the effects of retail participation in an emerging market context. Our findings suggest that individual traders, acting predominantly as noise traders, do not enhance price discovery and instead contribute to reduced market liquidity.

We further address potential self-selection concerns using a two-stage Heckman selection model, and our findings remain robust across various regression specifications. Importantly, the results correcting for selection bias indicate that unobservable factors are unlikely to be driving our conclusions, further strengthening the validity of our analysis. Moreover, our corrected results showed an even stronger negative relationship between individual trading intensity and market outcomes, both in economic magnitude and statistical significance.

Taken together, our results support the hypothesis that individual traders are generally uninformed, do not contribute to improved price discovery, and impede stock liquidity. These findings have important implications for policymakers and market regulators, particularly in emerging markets. Encouraging increased institutional participation could potentially enhance market liquidity and price efficiency by counteracting the negative effects of noise trading by individual investors. Finally, it is important to note that individual traders, despite our findings regarding their negative impact on liquidity and price discovery, still play a critical role in promoting retail participation and market accessibility, particularly in emerging markets like Kuwait, where institutional trading is relatively less dominant. Their activity fosters broader engagement within the financial system, enhancing market liquidity and depth in the absence of traditional intermediaries such as market makers, thereby contributing to the overall vibrancy and inclusivity of the market. Future research could further explore the role of regulatory changes, such as the introduction of market makers, in mitigating the adverse impacts of retail trading on liquidity and overall market efficiency in emerging markets.

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