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Liquidity, liquidity risk, and information flow: Lessons from an emerging market

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ABSTRACT

This paper examines the role of public and private information flows in intraday liquidity and intraday liquidity risk in the Tunisian stock market. Our empirical results are based on ARMA and GARCH-type models and show that, for major Tunisian stocks, gradually elapsed public information together with gradually elapsed private information in the market is the dominant factor in liquidity improvements in the Tunisian stock market. Liquidity improvements are generated by a decrease in the bid-ask spread accompanied by an increase in the depth at best limit. Our results clearly indicate that the arrival of public information in a sequential manner is the dominant factor generating increases in liquidity risk related to the bid-ask spread, while the advent of private information in a contemporaneous manner is the dominant factor generating increases in liquidity risk related to the depth at best limit. Additionally, our results show that liquidity risk persistence disappears when trading volume and order imbalance are included as explanatory variables in the conditional variance equation.

1. Introduction

The market microstructure theory has challenged the fundamental assumption of the efficiency theory, which assumes that hazard is the main determinant of asset price. Anderson (1996) suggests that the market microstructure theory shows that asset returns are generated from new information arriving on the market. Pioneering studies on the microstructure theory initially investigated the impact of trading volume on liquidity, particularly in the stock markets of developed countries. Lamoureux and Lastrapes (1990) considered trading volume a latent measure of public information. The authors show that the public information may be unequally accessible among market actors and may be interpreted differently. The authors also note that the diffusion of information in the market motivates investors to conduct transactions (purchases and sales). Many researchers have attempted to provide evidence of the relationship between return and return volatility with variables measuring transaction activities. The intuition concerning this relationship is based on two theoretical explanations: The mixture of distribution hypothesis (MDH)[1] and the sequential information arrival hypothesis (SIAH).[2] According to these

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[1] This hypothesis was be developed by Clark (1973).
[2] This assumption was developed by Copeland (1976).

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assumptions, larger, active markets are usually more liquid, and more frequently traded stocks have lower bid-ask spreads (Demsetz, 1968). According to Demsetz (1968), the results are a consequence of competitive intermediation. Higher transaction demand leads to more profit for dealers and hence cheaper provision of liquidity services. Additionally, lower costs naturally elicit more trade, as in any other product market. Underlying this view is the concept of liquidity as the output of a sector with access to a particular intermediation technology. The same conclusion is verified in some classical models of asymmetric information. Kyle (1985) shows that the equilibrium in the game between liquidity suppliers and informed traders requires that informed demand (and hence volume) scales with uninformed demand, while illiquidity (Kyle's lambda) is inversely proportional to the scale of uninformed demand because more noise renders total order flow less informative. Therefore, more volume implies higher liquidity. The same result is verified in a third class of model. Lippman and McCall (1986) suggest that search activity, for whatever reason, reduces liquidity.

However, the lack of a dynamic relationship between liquidity and information flow (mainly the volume of information flow) constitutes a challenge for the literature. During the last three decades, many researchers have attempted to analyze the relationship between liquidity, liquidity risk, and information.

The initial literature investigated the relationship between liquidity, liquidity risk, and traded volume. Many studies have shown a negative relationship between bid-ask spread as a price proxy for liquidity and trading volume (Bagehot, 1971; Copeland and Galai, 1983; Glosten and Milgrom, 1985; Kyle, 1985). Other researchers have attributed the depth of impact on trading volume to quantity-proxy of liquidity. Lee et al. (1993) showed that market makers protect themselves against the arrival of informed investors by increasing the bid-ask spread. In this situation, the market makers must also reduce the depth at best limit. The authors showed that a high trading volume generated an increase in the bid-ask spread and a decrease in the depth at best limit and, consequently, a deterioration in liquidity. More recently, Vo (2007) used intraday data from the Toronto stock market during the period September 1999 to November 1999. The author showed that trading volume is inversely related to both the quoted bid-ask spread and the effective bid-ask spread. However, trading volume is directly related to depth at best limit. This result implies that a high trading volume generates significant liquidity. Chen and Wu (2008) affirmed that depth at best limit cause-grangers the trading volume while the trading volume does not cause-granger depth at best limit. Chung et al. (2009) revealed a positive relationship between trading volume and liquidity in the Korean stock market. In the London stock market, Kyaw and Hillier (2011) showed that, for large companies, an increase in trading volume generates a decrease in the proportional bid-ask spread and hence an improvement in liquidity. For small companies, an increase in trading volume causes an increase in the proportional bid-ask spread and, therefore, a deterioration in liquidity. Chai et al. (2010) clearly explained the effect of trading characteristics on six liquidity measures in the Australian stock market. They showed that trading volume is the main determinant of liquidity. In the same market, Frino et al. (2011) tested the impact of trading halts on liquidity. The authors showed that this type of trading increases bid-ask spreads and reduces market depth at the best quotes in the immediate post-halt period. The results of this study illustrate that trading halts deteriorate market quality in markets that operate with open electronic limit order books. Fathi et al. (2012) investigated the effect of transaction activity measurements (price, return volatility, and trading volume) on liquidity. The authors found evidence that trading volume affects liquidity in the Tehran stock market. Malinova and Park (2013) studied the impact of the organization of trading on volume, liquidity, and price efficiency in a quote-driven dealer market and an order-driven limit order book. They showed that the trading volume released in a limit order market is higher, making this system most attractive for trading venues. More recently, Cao and Petrasek (2014) supported the hypothesis that, in the US context, institutional ownership affects the liquidity risk of stocks differently than individual ownership. Stocks held by institutions, on average, have lower liquidity risk than stocks held by individual investors during the period from 1990 to 2012. Referring to the NYSE ReTrac EOD database between March 15, 2004 and December 31, 2011, Wang and Zhang (2015) showed that heavily traded stocks by individual investors have higher liquidity. The positive effect of individual investor trading on stock liquidity is stronger for firms with greater information asymmetry, consistent with individual investor trading that reduces information asymmetry. These results suggest that trading volume generated by the individual investor improves stock liquidity by reducing information asymmetry.

Such studies have focused only on the traded volume (public information) and have ignored the private information and the trading direction in the analysis of the relationship between liquidity, liquidity risk, and information flow.[3] The second strand of literature considers public and private information in analyses of the relationship between asset return and information flow. Chan and Fong (2000) and Chordia et al. (2002) suggested that order imbalance might be a proxy for private information. The authors showed that the existence of order imbalance obliges market makers to move away from their optimal inventory position. When the deviation is significant, the associated costs will also be significant. To overcome this problem, the market makers adjust the bid-ask spread to attract the orders back to their optimal inventory position. This intuition coincides with the adverse selection theory: the order flow imbalances contribute to increasing costs generated by incorrect positioning inventory from market makers (Stoll, 1978; Ho and Stoll, 1981). From an empirical perspective, few studies have examined the relationship connecting order imbalance with the dimension-quantity of liquidity. Shen and

[3] Chordia et al. (2001) adequately explained the limits of trading volume as follows. Given a quantity of 1,000,000 traded shares, there are many possible situations. In the first case, the traded quantity can be interpreted as 1,000,000 sold shares, or it can be interpreted as 1,000,000 purchased shares. In the second case, the quantity may be divided into 500,000 shares initiated by sellers and 500,000 shares initiated by buyers. The authors suggested that, for each case, there are different implications for price and for liquidity.

Starr (2002) showed that order imbalance is characterized by a positive effect on the bid-ask spread and a negative effect on the depth at best limit. Chordia et al. (2002) showed that order imbalance is significantly associated with changes in daily liquidity in the case of the US stock market. This also implies that the excess of purchases or sales is a determinant of additional next trading volume in the explanation of liquidity. Ke et al. (2006) showed that, during July 2004 to December 2004 for the Taiwan stock market, order imbalance had a positive influence on the bid-ask spread and a negative influence on the depth at best limit.

More recently, Dey and Radhakrishna (2013) investigated the NYSE. The authors showed that the probability of informed trading (PIN)[4] as a proxy for private information is a significant determinant of bid-ask spreads for a sample of 65 listed securities.

This paper investigates the association between information flow and two other concepts, liquidity and liquidity risk, using a set of high-frequency data. Empirically, we use time series regression, as ARMA and GARCH family models, on a dataset of 38 stocks listed on the Tunisian stock market (TSM) from October 2008 to June 2009. The main results of this paper show the important effect of the information flow on the liquidity and liquidity risk of securities in the TSM. Then, we prove that both public and private information flows are dominant factors in liquidity improvements in the TSM. We note, also, that the arrival of public information in a sequential manner is the dominant factor generating an increase in liquidity risk related to the bid-ask spread. The contemporaneous private information arrival is the dominant factor generating an increase in liquidity risk related to the depth at best limit.

Our works contribute to the existing literature in several ways. First, previous works have been interested mostly in developed countries, and few studies address emerging markets (such as the Middle East and Asia). The subject of this study has not been examined in relatively illiquid markets such as those in North Africa and the TSE. Second, contrary to previous studies, we consider the effect of both public and private information on several alternative measures of liquidity and liquidity risk in our analysis. Third, the main contribution of this study is to investigate the dynamic interactions between information flow and the first and the second moments (mean and variance) of stock liquidity distributions. Particularly, the examination of the significance of information flow can be justified by the lack of studies addressing the combined effect of public and private information on liquidity and liquidity risk and focusing on the effect of lagged information spill over.

The remainder of this article is structured as follows. Section 2 discusses the Tunisian stock market, the description of the data, and the market structure. Section 3 discusses our methodology specifications. The empirical findings are presented in Section 4. Section 5 discusses the main findings and presents concluding remarks.

2. Market structure and data

2.1. Market structure

The Tunisian stock exchange market (TSEM) is a centralized market, governed by the orders of and controlled by the Council of Financial Markets (CFM). The TSEM was organized by the Law on Financial Market Reorganization, No. 94-117, dated 14 November 1994. However, this legislation was found to be inadequate for the development of the TSEM, which motivated the authorities to modify the earlier law to Law No. 99-92 on 17 August 1999 after the recovery of the financial market. In a similar context, Law No. 2005-96 on the Strengthening of Financial Security and Transparency was passed on 18 October 2005. In addition to the legal reforms, an electronic trading system called SUPER-CAC UNIX was introduced on 25 October 1996. On 3 December 2007, the TSE launched a new version of the electronic trading system, V900, which was developed by Atos Euronext.

In October 2008, the TSE extended the duration of the trading session from 2 h to 5 h 10 min. The main market is now open from 09:00 am to 02:10 pm. The purchase and sell orders submitted by investors that are introduced into the quotation system are confronted depending on the degree of liquidity in two ways: the fixing quotation and the continuous quotation mode. All these reforms contributed to enhancing the stock market, increasing the trading activity, and restoring the investor confidence, which led to an evolution in the liquidity. The trading day in the Tunisian stock market pre-opens from 09:00 am to 10:00 am. During this period, the purchase orders and sales orders are entered into the system without affecting the transactions. As soon as the market opens, the system determines an opening price that will be used only for the transactions made by the opening auction at 10:00 am. After the opening of the market and during the continuous session that lasts from 10:00 am to 02:00 pm, the introduction of an order in the system can generate an instantaneous transaction when there is an opposite order.

2.2. Data

In this study, we use a sample of 38 shares quoted on the continuous trading session during the period October 2008 to the end of June 2009. The TSM contains 50 securities, we exclude 12 shares quoted on fixing quotation because the law of supply and demand is not involved in this type of trading.

[4] PIN, another control variable, denotes information content in order imbalance

Table 1
Descriptive statistics over the period October 2008–June 2009.

Variables	Value
Number of companies	38
Trading days	184
Number of transactions	240,564
Quantities of transactions	121,399,567
Daily average of the number of transactions by stock	34
Total maximum quantity traded for Attijari Bank	20,163,175
Total minimum quantity traded for BTE-ADP	119,409
Average daily of trading volume by the action	17,506
Number of purchase orders submitted	170,413
Quantities of stocks submitted by purchase orders	130,262,717
Number of sale orders submitted	158,099
Quantities of stocks submitted by sale orders	130,616,034

The period of study is justified for two reasons. First, prior to October 2008, the trading session on the TSM ran from 9 am until 12:10 pm. After October 2008, the TSM extended the duration of the trading session by 2 h for a duration of 5 h and 10 min. Since then, the main market has operated from 9 am to 2:10 pm. This new market situation prompted us to select the period 2008–2009 to investigate the behavior of the market following the change in the trading session. Thus, the use of intraday data is favored by the introduction of the electronic SUPERCAC quotation system in 1998, which improved the speed of price adjustment in the stock market. Market transparency has also increased significantly following the promulgation of the financial security information law in 2005 by the Financial Market Council. Second, despite that this period is an exceptionally volatile period in the history of stock market, the Tunisian stock market has experienced an increase of its market capitalization (Fig. A.1, Appendix A).

Two intraday files compose our database[5]: a trading (transaction) file and the quotes file. The transaction file contains the intraday transaction prices and quantities along with the code of each stock on the transaction system, the date, and the transaction time. The second file includes the set of limit order purchases and sales along with the code of each purchase order and sale order, the date and time of entry of the order, the ASK price, the BID price entered by the intermediary stock exchange, and the quantity appropriate for each ASK price and BID price.

The details of this descriptive analysis are presented in Table 1. To conduct our research; this table shows that the daily average of trading volume per session during our retained period is about 34 transactions. The average number of transactions traded per day is 17506. In addition, it is clear that the number of sale orders exceeds the number of purchase orders. The total amount of transactions performed during the period of study was 121,399,567. The total maximum quantity negotiated is 20,163,175 (Attijari Bank) while the total minimum quantity negotiated is 119,409 (BTE-ADP).

2.2.1. Variables definitions

In our analysis, we use two liquidity indicators: the bid-ask spread and the depth at-best limit. Contrary to previous studies such as Chordia et al. (2001), Brockman and Chung (2002), and Pukthuanthong-Le and Visaltanachoti (2009), we use the actual value and not the relative variations in order to represent liquidity. This is justified for two reasons. (i) Certain equity securities listed on the TSM were relatively illiquid. (ii) We obtained a series that suffered from missing interval observations. Therefore, applying Chordia et al. (2001) method on our data would not produce consistent results. The quoted spread represents the difference between the best of limited price of purchase and the best of limited price of sale.

$$QSPR_t = [(P_B) - (P_A)] \tag{1}$$

where $QSPR_t$ represents the quoted spread at interval t; P_B is the best limit price to buy (BID) at interval t; and P_A is the best limit price to sell (ASK) at interval t. Thus, the depth indicates the quantity available for purchase and sale for each price level at a given instant.

$$DEP_t = \frac{(Q_B + Q_A)}{2} \tag{2}$$

where DEP_t is the depth at interval t; Q_B is the quantity available at the purchase price at interval t; and Q_A is the quantity available at the selling price at interval t.

The liquidity risk is defined as the risk of liquidity deterioration when investors need to liquidate their positions. Acharya and Pedersen (2005) define liquidity risk as being the possibility that liquidity might disappear from the market and therefore not be available when we need it. Indeed, liquidity risk[6] captures the gain or loss realized by the investor when there is a variability of market liquidity. Recently, Papavassiliou (2013) affirmed that liquidity risk could be defined as being a type

[5] We note that authors were funded by their proper the database.
[6] Dowd (1998) advanced two types of liquidity risk. The first one is the normal liquidity risk which increase according to transactions on markets characterized by a little level of liquidity. The second type is called the crisis liquidity risk which implies that liquidity risk arising during stock market

of risk associated with the inability to buy and sell assets at the market price at any desired moment. In this line, Tsuji (2003) affirmed that the volatility is represented the best factor for capturing the risk of crash liquidity. He added that the measurement of this volatility require to use the ARCH/GARCH family models developed by Engle (1982), Bollerslev (1986), and Nelson (1991). This kind models is used to take into account for various proprieties such as, persistence, asymmetric volatility and conditional heteroscedasticity.

Based on previous literature, we use the trading volume as proxy of the public information. The information is qualified as public when it is diffused publically to different agents (Morris and Shin, 2004). The trading volume indicates the number of stocks traded in each interval. The trading volume measure is determined the following formula[7]:

$$V_{it} = [100 * Ln(NAE_{it})] \tag{3}$$

where V_{it} represents the trading volume of stock i in interval t. NAE_{it} represents the number of stocks traded for stock i in interval t.

Finally, the determination of order imbalance requires the knowledge about whether a transaction was initiated by a buyer or a seller. The data set usually available does not provide information about the initiator of a transaction. Lee and Ready (1991) proposed an algorithm based on quotes and transactions data to determine the initiator of a transaction. The algorithm proceeds in three steps: (i) transactions which occur at prices higher [lower] than the mid-quote are classified as being buyer-initiated [seller-initiated]; (ii) transactions which occur at a price that equals the mid-quote but is higher [lower] than the previous transaction price are classified as being buyer-initiated [seller-initiated]; (iii) transactions which occur at a price that equals both the mid-quote and the previous transaction price but is higher [lower] than the last different transaction price are classified as being buyer-initiated [seller-initiated]. After applying the algorithm of Lee and Ready (1991) on our data transactions and quotes, we should then determine the order imbalance variable. Hence, the most commonly formula used in microstructural studies in order to detect this variable is as follows:

$$OIB_{it}\left[\sum_{it=1}^{N} NTA_{it} - \sum_{it=1}^{N} NTV_{it}\right] \tag{4}$$

where OIB_{it} represents the order imbalance on stock i in interval t. NTA_{it} represents the number of buyer-initiated trades on stock i in interval t. NTV_{it} represents the number of seller-initiated trades on stock i in interval t.

2.2.2. Summary statistics

Table A.1 (Appendix A) provides descriptive statistics of intraday quoted spread, intraday depth-at-best-limit, intraday trading volume and intraday order imbalance series of the 38 studied individual stocks. This table shows that the distribution of different sets of quoted spread, depth-at-best-limit, trading volume and order imbalance follow non-normal distributions since the Jarque–Bera test statistics is significant at the 1% level for all variables. Similarly, these distributions have an asymmetrical distribution because the Skewness statistics is different from 0 for all variables. In addition, the kurtosis values are different from 3 for all variables. This shows that for all series the distribution of the intraday quoted spread, the intraday depth-at-best-limit, the trading volume and the order imbalance have fatter tails and sharper peaks at the center compared with normal distribution. Not surprisingly, these preliminary results are typically consistent with previous investigations on the emerging stock markets' dynamics.

After taking into account the normality hypothesis, we implemented some unit root tests. With reference to the Augmented Dickey–Fuller (ADF) and the Phillips–Perron (PP) unit root tests, we can undoubtedly reject the hypothesis of unit root for the whole of our sample. These unit root tests are important in time series analysis as the choice of the techniques and procedure for further analysis and modeling of series depends on their order of integration. Table A.2 (Appendix A) summarizes the empirical results of applying these tests showing that the null hypothesis of the existence of a unit root is rejected for all series. All series showed stationary behavior at the 1%, 5%, 10%. In fact, we note that without taking into account the presence of unit root in the variables, the analysis may produce spurious results.

3. Empirical methodology

We apply uni-variate ARCH models to consider the phenomena of asymmetry and volatility persistence. These types of models assume the variance of the current error term or innovation to be a function of the actual size of the previous periods' error terms: often the variance is related to the squares of the previous innovations and some exogenous variables that contribute to the explanation of the dependent variable. In our analysis, the GARCH models allow us to model the conditional mean and the conditional variance for our two dependent variables: each bid-ask spread series and each depth series. In modeling the means of these variables, we follow the process of Box and Jenkins (1976) to select the optimal model from the ARMA(p, q) candidate specifications. However, to model the variance of our dependent variables, we estimate the

crises where the market loses its current liquidity level: investor who liquidates its positions registers so a loss more important than during normal circumstances.

[7] The reason for using the natural logarithm is to normalize this variable so as not to fall into fallacious estimates.

variety model of GARCH (such as: GARCH(p, q) process of Bollerslev (1986); EGARCH(p, q) process of Nelson, 1991; TGARCH(p, q) process of Zakoian (1994), or PGARCH(p, q, δ) process of Ding et al., 1993). We then select the optimal specification based on information criteria.

Our empirical methodology is divided into two parts. First, we examine the effect of information flow on liquidity in the TSE. Second, we investigate the effect on liquidity risk.

3.1. The relationship between information flow and liquidity

We first investigate the effect of public and private information on liquidity. We include contemporaneous trading volume and contemporaneous order imbalance as proxies for public and private information in the bid-ask spread conditional mean and in the depth conditional mean, respectively. Many studies have considered the impact of contemporaneous information spillover only. Therefore, we extend the previous literature by examining the effect of the lagged information spillover. The study of the lagged context is important because the detection of a significant relationship between lagged information flow and liquidity and risk liquidity is synonymous of market inefficiency and, therefore, a reflection of the forecasting ability of the trading volume and the order imbalance. Empirically, we allow lagged trading volume and the lagged order imbalance as proxies for public information and private information, respectively, to enter the bid-ask spread and the depth conditional mean equations. The liquidity measure is determined for the two variables intraday spread and intraday depth-at-best-limit according the process of ARMA(p, q) identification. AIC and SIC are used to choose the final models from various possible ARMA(p, q). The ARMA(p, q) estimation results for stock return and the diagnostic tests for these selected models are displayed in Table A.3, Appendix A.

For the link between liquidity spillover and public information, the regression models are written as:

$$\begin{cases} L_{t,i} = \alpha + \beta PubINF_{t,i} + \varepsilon_{i,t} & (5) \\ L_{t,i} = \alpha + \beta PubINF_{t-1,i} + \varepsilon_{i,t} & (6) \end{cases}$$

where $L_{t,i}$ represents the bid-ask spread and the depth, $PubINF_{t,i}$ is the contemporaneous trading volume, and $PubINF_{t-1,i}$ is the lagged trading volume.

For the bid-ask spread, the parameter β informs us of the effect of public information arrival on liquidity. Additionally, a significant and positive (negative) β implies that public information arrival generates a deterioration in liquidity (an improvement of liquidity). However, in the case of depth (Eq. (6)), a significant and positive (negative) β implies that public information arrival generates an improvement in liquidity (a deterioration of liquidity).

Concerning the relationship between liquidity spillover and private information, the regression models are written as:

$$\begin{cases} L_{t,i} = \alpha + \beta PivINF_{t,i} + \varepsilon_{i,t} & (7) \\ L_{t,i} = \alpha + \beta PivINF_{t-1,i} + \varepsilon_{i,t} & (8) \end{cases}$$

where $L_{t,i}$ represents the bid-ask spread and the depth, $PrivINF_{t,i}$ represents contemporaneous order imbalance, and $PrivINF_{t-1,i}$ represents the lagged order imbalance.

For the bid-ask spread, the parameter δ informs us of the effect of private information arrival on liquidity. A significant and positive (negative) effect implies that private information arrival contributes to a deterioration in liquidity (an improvement in liquidity). However, with respect to depth, a significant and positive (negative) effect implies that private information arrival generates an improvement in liquidity (a deterioration in liquidity).

To account for the interaction between the liquidity spillover and public and private information, the regression models are written as:

$$\begin{cases} L_{t,i} = \alpha + \beta PubINF_{t,i} + \delta PivINF_{t,i} + \varepsilon_{i,t} & (9) \\ L_{t,i} = \alpha + \beta PubINF_{t,i} + \delta PivINF_{t-1,i} + \varepsilon_{i,t} & (10) \end{cases}$$

For the bid-ask spread, significant and positive (negative) parameters (β and δ) imply that public and private information arrival contributes to a deterioration in liquidity (an improvement in liquidity). However, for depth, significant and positive (negative) parameters (β and δ) illustrate that public and private information arrival generate an improvement in liquidity (a deterioration of liquidity).

3.2. The relationship between information flow and liquidity risk

This section investigates the effect of public and private information on liquidity risk. Empirically, we incorporate contemporaneous trading volume and contemporaneous order imbalance – as a proxy for public information and private information – in both the bid-ask spread and depth conditional variance equations. The conditional variance specification is determined from the various GARCH model estimations using the information criteria. Appendix B presents the estimated specifications.

Previous studies investigating the importance of contemporaneous information spillover did not provide an extensive overview of the determinants of liquidity risk. We complete the existing microstructure literature by providing evidence of the significance of lagged information spillover and contemporaneous information spillover.

Thus, we analyze the relationship between liquidity risk spillover and public information after the estimate of the following regression models:

$$\begin{cases} LR_{t,i} = \alpha + \beta PubINF_{t,i} + \varepsilon_{i,t} & (11) \\ LR_{t,i} = \alpha + \beta PubINF_{t-1,i} + \varepsilon_{i,t} & (12) \end{cases}$$

where $LR_{t,i}$ represents the bid-ask spread volatility and the depth volatility, $PubINF_{t,i}$ represents the contemporaneous trading volume and $PubINF_{t-1,i}$ represents the lagged trading volume.

For the bid-ask spread, the parameter β informs us of the effect of public information arrival on liquidity risk (a decrease in liquidity risk). A significant and positive (negative) effect implies that public information arrival generates an increase in liquidity risk (a decrease in liquidity risk). Similarly, for depth, a significant and positive (negative) parameter β indicates that public information arrival generates an increase in liquidity risk (a decrease in liquidity risk).

To account for the interaction between liquidity risk spillover and private information, we estimate the following regression models:

$$\begin{cases} LR_{t,i} = \alpha + \delta PivINF_{t,i} + \varepsilon_{i,t} & (13) \\ LR_{t,i} = \alpha + \delta PivINF_{t-1,i} + \varepsilon_{i,t} & (14) \end{cases}$$

where $LR_{t,i}$ represents the bid-ask spread volatility and the depth volatility, $PrivINF_{t,i}$ represents the contemporaneous order imbalance, and $PrivINF_{t-1,i}$ represents the lagged order imbalance.

For bid-ask spread, the significant and positive (negative) parameter δ informs us that private information arrival increases (decreases) the liquidity risk. Similarly, for depth, a significant and positive (negative) parameter δ implies that private information arrival generates an increase in liquidity risk (a decrease in liquidity risk).

Then, for the link between liquidity risk spillover and public and private information, the regression models are written as:

$$\begin{cases} LR_{t,i} = \alpha + \beta PubINF_{t,i} + \delta PivINF_{t,i} + \varepsilon_{i,t} & (15) \\ LR_{t,i} = \alpha + \beta PubINF_{t-1,i} + \delta PivINF_{t-1,i} + \varepsilon_{i,t} & (16) \end{cases}$$

where $LR_{t,i}$ represents the bid-ask spread volatility and the depth volatility, $PubINF_{t,i}$ and $PrivINF_{t,i}$ represent the contemporaneous trading volume and the contemporaneous order imbalance, and $PubINF_{t-1,i}$ and $PrivINF_{t-1,i}$ represent the lagged trading volume and the lagged order imbalance.

For the bid-ask spread, significant and positive (negative) parameters β and δ imply that the public and private information arrival contribute to a liquidity risk increase (decrease). For depth, significant and positive (negative) parameters β and δ imply that public and private information arrival generates an increase in liquidity risk (a decrease in liquidity risk).

4. Empirical results

4.1. Modeling the intraday quoted spread and intraday depth

Before investigating the relationship results between information flows with liquidity and liquidity risk, we first determine the relevance specifications for modeling the liquidity and liquidity risk. The results of liquidity specifications are presented in Table A.3 (Appendix A). Overall, the results suggest that the application of the Ljung–Box test shows that the null hypothesis of no autocorrelation is accepted for 89% of quoted spread series and for 76% of depth-at-best-limit series and the application of the LM-ARCH test supports the reject of the null hypothesis of homoscedasticity in favor of alternative heteroscedasticity conditional for the majority of return series. On the one hand, this latter result confirms the reject of the hypothesis of the absence of ARCH effect. This indicates the presence of volatility clustering. On the other hand, it is true that there is no significant ARCH effect in the rest of series but it does mean that there is still less GARCH effect. In such a context, the presence of asymmetry detected by the Skewness statistics and the existence of ARCH effect require the modeling of different quoted spread series and depth-at-best-limit series through the application of uni-variate ARCH models. Similar to several previous empirical studies, the presence of ARCH effect and the phenomenon of asymmetry necessarily need the use of non-linear specifications to model the conditional variance.

Table A.4 (Appendix A) presents the results of the relevance specifications for the modeling of the volatility based on the intraday bid-ask spread and the intraday depth at best limit.

For the bid-ask spread, our results show that, for 26 shares (68% of the total sample), the degree of persistence (measured by $\alpha_1 + \beta_1 + 1/2\gamma_1$) exceeds one. Only four shares (11% of all shares) have a degree of persistence between 0.9 and 1, and 21% of all shares are characterized by a degree of persistence less than 0.9 (see, Table A.4, Appendix A). This result highlights the high degree of persistence of the bid-ask spreads in the TSM. Additionally, a large change in bid-ask spread tends to

Table 2
The regression results for the impact of information flow on liquidity (the bid-ask spread dimension).

	Bid-Ask spread							
	Panel A Public information		Panel B Private information		Panel C Public information and private information			
	INF Pub	INF PUB – 1	INF Priv	INF Priv – 1	INF PUB	INF PUB – 1	INF Priv	INF Priv – 1
Number of firms with a positive coefficient and *t*-statistic significant (%)	35(92%)	6(16%)	6(16%)	10(26%)	36(95%)	4(11%)	16(42%)	14(37%)
Number of firms with a positive coefficient and *t*-statistic non-significant (%)	3(8%)	2(5%)	5(13%)	6(16%)	2(5%)	3(8%)	5(13%)	4(11%)
Number of firms with a negative coefficient and *t*-statistic significant (%)	0(0%)	26(68%)	18(47%)	18(47%)	0(0%)	27(71%)	6(16%)	16(42%)
Number of firms with a negative coefficient and *t*-statistic non-significant (%)	0(0%)	4(11%)	9(24%)	4(11%)	0(0%)	4(11%)	11(29%)	4(11%)

be followed by a large change, and a small change tends to be followed by a small change. Table A.4 shows that all bid-ask spreads are characterized by an asymmetric propriety obtained according to a variety of models. In 14% of the cases (five shares), the bid-ask spread volatility is modeled by the GJR-GARCH model. The asymmetry coefficient γ_k is statistically significant and negative in five cases. We model 50% of series through an E-GARCH model. The coefficient γ_k is statistically significant and positive in 19 cases, indicating that a negative shock generates less volatility than a positive shock. Therefore, we conclude the existence of the leverage effect in the case of TSM. For the PGARCH (1,1) process, the empirical estimation of the models show that the asymmetry coefficient γ_k is significant and negative in 12 cases, implying the existence of a significant leverage effect. Similarly, the parameter power δ_1 is significant and takes a positive value in all cases, showing that a negative shock has a substantial effect on volatility compared to a positive shock.

For the depth at best limit, there are 17 shares (45% of the total sample) with a degree of persistence that exceeds one, 13 shares (34% of all shares) with a degree of persistence between 0.9 and 1, and eight remaining shares (21% of all shares) with a degree of persistence less than 0.9. This result confirms the persistence of shock volatility in the TSM. For the asymmetry phenomenon, 89% of the series of depth at best limit follow asymmetric modeling. Table A.4 shows that 55% of the sample follows a TGARCH process. The asymmetry coefficient γ_k is statistically significant and positive in nine cases, but significant and negative in six cases. This result indicates that the asymmetry properties of shocks originate from depth at best limit. Similarly, 13% (five shares) of the depth at best limit series follows a GJR-GARCH (1,1) process. The estimation of this type of asymmetric specification asserts that the asymmetry coefficient γ_k is statistically significant and negative in two cases. For the remaining three shares, the asymmetry coefficient is positive and statistically significant. The results in Table A.4 show that 13% of the depth at best limit series are modeled according to EGARCH (1,1).[8] We note that three shares (SOTUVER, BTEADP, and POULINA) are modeled by PGARCH (1.1), asymmetry coefficient γ_k is significant and positive in two cases, and significant and negative in one case. These findings confirm the existence of a significant leverage effect in the TSM.

4.2. The results of the relationship between liquidity and information flow

4.2.1. The case of public information flow only

For the bid-ask spread, the estimation of Eqs. (5) and (6) (Table 2, Panel A) show that the contemporaneous trading volume coefficient ($PubINF_{t,i}$) is statistically significant and positive for 92% of the entire sample (35 shares), whereas it is statistically non-significant and positive in three cases (8%). The positive coefficients of trading volume indicate that an increase in trading activity enhances the bid-ask spread and, therefore, the deterioration of liquidity.[9] This illiquidity indicates that the trading process in the TSM is slow and expensive. The difficulty in trading will be traduced by panic and insolvency behavior by the investor. Because of the illiquidity, the inventory and transaction costs will increase. Moreover, our empirical investigations reveal that the lagged trading volume coefficient ($PubINF_{t,i-1}$) is statistically significant and

[8] Similarly, the coefficient γ_k is statistically significant and positive in two cases and statistically significant and negative for three shares. This result illustrates that positive shocks generate less volatility than negative shocks.

[9] Therefore, our findings confirm theoretically the explanation of Easley and O'Hara (1992) and, empirically, the results of Lee et al. (1993), but the findings contradict the results determined by Vo (2007).

Table 3
The regression results for the impact of information flow on liquidity (the depth at best limit dimension).

	Depth at-best-limit							
	Panel A Public information		Panel B Private information		Panel C Public information and private information			
	INF Pub	INF PUB – 1	INF Priv	INF Priv – 1	INF PUB	INF PUB – 1	INF Priv	INF Priv – 1
Number of firms with a positive coefficient and *t*-statistic significant (%)	38(100%)	31(82%)	7(18%)	13(34%)	37(97%)	34(89%)	13(34%)	8(21%)
Number of firms with a positive coefficient and *t*-statistic non-significant (%)	0(0%)	0(0%)	2(5%)	13(34%)	0(0%)	1(3%)	8(21%)	14(37%)
Number of firms with a negative coefficient and *t*-statistic significant (%)	0(0%)	4(11%)	29(76%)	5(13%)	0(0%)	1(3%)	6(16%)	7(18%)
Number of firms with a negative coefficient and *t*-statistic non-significant (%)	0(0%)	3(8%)	0(0%)	7(18%)	1(3%)	2(5%)	11(29%)	9(24%)

positive in six cases and statistically significant and negative in 26 cases. This finding implies that an increase in the lagged trading volume reduces the bid-ask spread and, therefore, improves liquidity for almost 68% of our sample. The decrease in the best ask price and the increase in the best bid price will encourage investors to conduct transactions. The sequential flow of public information on the TSM may improve market liquidity for most shares.

For the depth at best limit, the empirical regression of Eqs. (5) and (6) (Table 3, Panel A) indicates that the contemporaneous trading volume coefficients $PubINF_{t,i}$ are statistically significant and positive for all securities. This implies the existence of a positive contemporaneous relationship between trading volume and depth at best limit and hence an improvement in liquidity in the TSM. This result is contrary to the findings of Kavajecz (1999) and Lee et al. (1993), but confirms the empirical results of Vo (2007). This result is explained by the need for liquidity, which motivates investors to conduct various purchases and sales orders despite the risk of adverse selection. Then, our empirical results reveal that the coefficient of lagged trading volume $PubINF_{t,i-1}$ is statistically significant and positive in 31 cases and significant and negative in four cases, whereas it is non-significant and negative in three cases. Therefore, an increase in lagged trading volume increases the depth at best limit and, consequently, improves liquidity. Based on this result, we consider the lagged trading volume a forecast indicator of securities liquidity.

4.2.2. The case of private information flow only

Table 2 (Panel B) presents the results for the bid-ask spread estimation specified in Eqs. (7) and (8). First, the contemporaneous order imbalance coefficient $PrivINF_{t,i}$ is statistically significant and positive in six cases, and significant and negative in 18 cases; however, it is statistically non-significant and positive in five cases and statistically non-significant and negative in nine cases. These results imply that the relationship between order imbalance and the bid-ask spread is mitigated. Therefore, an increase in order imbalance generates an improvement in liquidity in 47% of our sample, while an increase in the contemporaneous order imbalance causes a deterioration in liquidity for 18% of our sample.[10] Second, the empirical evidence indicates that the coefficient of lagged order imbalance $PrivINF_{t,i-1}$ is statistically significant and positive in 10 cases and statistically significant and negative in 18 cases, whereas it is statistically non-significant and positive in six cases and non-significant and negative in four cases. The link between order imbalance and the bid-ask spread is also mitigated. In this case, the ambiguity of the lagged relationship between order imbalance and liquidity does not allow investors to base their trading strategies on order imbalance as an indicator in predicting the level of liquidity in the TSM.

For depth at best limit in Table 2, Panel B reported the empirical findings of Eqs. (7) and (8). First, the coefficient of order imbalance $PrivINF_{t,i}$ is statistically significant and positive in seven cases from the total sample and significant and negative in 29 cases; however, it is non-significant in two cases. This result indicates that an increase in order imbalance decreases the depth at best limit and, consequently, deteriorates liquidity for a large part of our sample (74%). Our results confirm the findings of Ke et al. (2006) for the TSM. Second, the coefficient of lagged order imbalance $PrivINF_{t,i-1}$ is statistically significant and positive in 13 cases and significant and negative in 13 cases; however, it is non-significant and negative in seven cases and non-significant and positive in five cases. The effect of the lagged relationship between order imbalance and depth at

[10] Our results do not coincide with the theoretical foundations of Stoll (1978) and Spiegel and Subrahmanyam (1995) and, empirically, with the result of Ke et al. (2006) for the TSM.

best limit is ambiguous because only 34% of the sample shows that the increase in the lagged order imbalance generates a deterioration in liquidity. The sequential flow of private information also improves liquidity for 34% of our sample. The lagged order imbalance is not a relevant indicator for TSM investors in predicting long-term levels of liquidity.

4.2.3. The simultaneous flow of public and private information

Panel C in Table 2 presents the estimation results of Eqs. (9) and (10) related to the bid-ask spread. First, the results show that the contemporaneous coefficient of order imbalance ($PrivINF_{t,i}$) is statistically significant and positive in 16 cases (42%) and statistically significant and negative in six cases (16%), whereas it is statistically non-significant and positive in five cases (13%) and non-significant and negative in 11 cases (29%). This result confirms the ambiguous effect of private information (order imbalances) on liquidity (bid-ask spread). For the trading volume, the contemporaneous coefficient $PubINF_{t,i}$ is statistically significant and positive in 36 cases (95%) and not statistically significant and positive in two cases (5%). This finding indicates that public information flow represents the main source of illiquidity in the TSM. Second, our results suggest that the lagged order imbalance coefficient $PrivINF_{t,i-1}$ is statistically significant and positive in 14 cases (37%) and statistically significant and negative in 16 cases (42%). The coefficient is statistically non-significant and positive in four cases (10%) and non-significant and negative in four cases (10%). This result shows that the interaction between lagged order imbalances and bid-ask spread is not clear in the TSM. Concerning the trading volume, the estimated coefficient ($PubINF_{t,i-1}$) is statistically significant and positive for four cases (10%) and statistically significant and negative for 27 cases (71%); however, the coefficient is non-significant and positive in three cases (8%) and non-significant and negative in four cases (10%). For the majority of securities in the TSM, an increase in trading volume leads to a reduction in the bid-ask spread and, therefore, an improvement in liquidity. These empirical findings show that past public information on the Tunisian market dominates both contemporaneous and past private information in terms of the liquidity effect. Additionally, the investors can use the lagged trading volume to predict the level of liquidity in the TSM.

Panel C in Table 3 presents the results of Eqs. (9) and (10) related to the depth at best limit. First, the coefficient of order imbalance ($PrivINF_{t,i}$) is statistically significant and positive in 13 cases (35%) and significant and negative in six cases (16%); however, it is non-significant and negative in eight cases (21%) and non-significant and positive in 11 cases (29%). Panel C in Table 3 also shows that the coefficient of trading volume $PubINF_{t,i}$ is significant and positive in 37 cases (98%) in our sample, whereas it is non-significant and negative in one case (2%). Consequently, an increase in the contemporaneous order imbalance improves the liquidity (bid-ask spread) in 35% of our sample, whereas the increase in contemporaneous trading volume increases liquidity (the depth at best limit) for the majority of the sample. These findings indicate that the arrival of both contemporaneous public and private information has a clear effect on liquidity. Regardless, the effect of public information is more pronounced than the private information in the TSM.

Second, the coefficient of lagged order imbalance ($PrivINF_{t,i-1}$) is statistically significant and positive in eight cases (21%), and significant and negative in seven cases (19%), whereas it is non-significant and negative in nine cases (24%) and non-significant and positive in 14 cases (37%). The lagged public information variable for trading volume $P(ubINF_{t,i-1})$ is significant and positive in 34 cases (90%) and significant and negative in one case (2%), whereas it is non-significant and positive in one case (2%) and non-significant and negative in two cases (6%). These results highlight two main findings: (i) the ambiguous relationship between private information and liquidity in the TSM lagged order imbalance generates an improvement of liquidity for 21% of our sample, but a deterioration of liquidity for 18% of our sample, and (ii) past public information has a clear and consistent impact on liquidity in the TSM. More precisely, an increase in the lagged trading volume generates an increase in the depth at best limit and, therefore, an improvement in liquidity for 90% of our sample. Past public information dominates private information in terms of liquidity effect in the TSM. Overall, this finding confirms the intuition that investors can use lagged trading volume in their trading strategies to predict the level of liquidity in the TSM.

4.3. The results of the relationship between liquidity risk and information flow

4.3.1. The case of public information flow only

Panel A in Table 4 presents the estimation results of bid-ask spread volatility specified in Eqs. (11) and (12). First, the trading volume coefficient ($PubINF_{t,i}$) appears strictly significant and positive in 22 cases (58%), significant and negative in 14 cases (37%), and non-significant and negative in the two cases (5%). This empirical evidence indicates that new public information arrival in the Tunisian market increases the bid-ask spread volatility and, therefore, raises liquidity risk for 58% of the sample. The interaction between trading volume and liquidity risk is not clear. The rise in liquidity risk increases both the uncertainty in trading time and disability in the accurate evaluation of market tension. Consequently, the more this uncertainty matures, the greater the acceptance probability of an offer below expectations to avoid unexpected losses. Second, the lagged trading volume coefficient ($PubINF_{t,i-1}$) appears strictly significant and positive in 27 cases (71%), significant and negative in 10 cases (27%), and non-significant and negative in one case (2%). The validation of the relationship between lagged trading volume and bid-ask spread volatility confirms the role of trading volume as a prediction indicator of liquidity risk in 71% of the sample. As with contemporaneous trading volume, the greater the significance of liquidity risk, the greater the uncertainty and the acceptance probability that an offer below expectations will be important to avoid unexpected losses.

Panel A in Table 5 presents the estimation results of depth at best limit volatility specified by Eqs (11) and (12). First, the contemporaneous trading volume coefficient ($PubINF_{t,i}$) appears strictly significant and positive in 10 cases (27%), significant

Table 4
The regression results for the impact of information flow on liquidity risk (the bid-ask spread case).

	Bid-Ask spread							
	Panel A Public information		Panel B Private information		Panel C Public information and private information			
	INF Pub	INF PUB – 1	INF Priv	INF Priv – 1	INF PUB	INF PUB – 1	INF Priv	INF Priv – 1
Number of firms with a positive coefficient and *t*-statistic significant (%)	22(58%)	27(71%)	19(50%)	18(47%)	16(42%)	23(61%)	12(32%)	13(34%)
Number of firms with a positive coefficient and *t*-statistic non-significant (%)	0(0%)	0(0%)	3(8%)	3(8%)	5(13%)	1(3%)	6(16%)	11(29%)
Number of firms with a positive coefficient and *t*-statistic significant (%)	14(37%)	10(26%)	11(29%)	12(32%)	16(42%)	13(34%)	15(39%)	7(18%)
Number of firms with a negative coefficient and *t*-statistic non-significant (%)	2(5%)	1(3%)	5(13%)	5(13%)	5(13%)	1(3%)	5(13%)	7(18%)

Table 5
The regression results for the impact of the information flow on liquidity risk (the depth at best limit case).

	Depth at-best-limit Panel A Public information		Panel B Private information		Panel C Public information and private information			
	INF Pub	INF PUB – 1	INF Priv	INF Priv – 1	INF PUB	INF PUB – 1	INF Priv	INF Priv – 1
Number of firms with a positive coefficient and *t*-statistic significant (%)	10(26%)	17(45%)	25(66%)	19(50%)	10(26%)	16(42%)	15(39%)	12(32%)
Number of firms with a positive coefficient and *t*-statistic non-significant (%)	0(0%)	0(0%)	1(3%)	4(11%)	0(0%)	1(3%)	5(13%)	11(29%)
Number of firms with a positive coefficient and *t*-statistic significant (%)	27(71%)	20(53%)	10(26%)	11(29%)	27(71%)	20(53%)	9(24%)	7(18%)
Number of firms with a negative coefficient and *t*-statistic non-significant (%)	1(3%)	1(3%)	2(5%)	4(11%)	1(3%)	1(3%)	9(24%)	8(21%)

and negative in 27 cases (71), but non-significant and negative in one case (2%). This finding highlights the effect of contemporaneous trading volume in reducing the depth at best limit volatility for major securities in the TSM. Consequently, the uncertainty with respect to transaction time will be lower, and the ability to accurately evaluate the market stress will be greater. Second, the lagged trading volume coefficient ($PubINF_{t,i-1}$) is strictly positive and significant in 17 cases (45%), significant and negative in 20 cases (53%), and non-significant and negative in one case (2%). This result shows a significant effect of lagged trading volume and the depth at best limit volatility but with some mitigation. Hence, we must be prudent in interpreting this relationship. In this stage of the analysis, we cannot adopt this indicator as a predictor of future liquidity risk for the entire stock market.

4.3.2. The case of private information flow only

Panel B in Table 4 reports the estimation results for the bid-ask spread volatility specified in equations 13 and 14. First, the contemporaneous order imbalance coefficient ($PrivINF_{t,i}$) appears strictly significant and positive in 19 cases (50%), significant and negative in 11 cases (29%) and non-significant and positive in three cases (8%), whereas it is non-significant and negative in five cases (13%). These results illustrate that the instantaneous private information arrival increases the bid-ask spread volatility for 50% of our sample and consequently improves the liquidity risk. It is significant that an increase

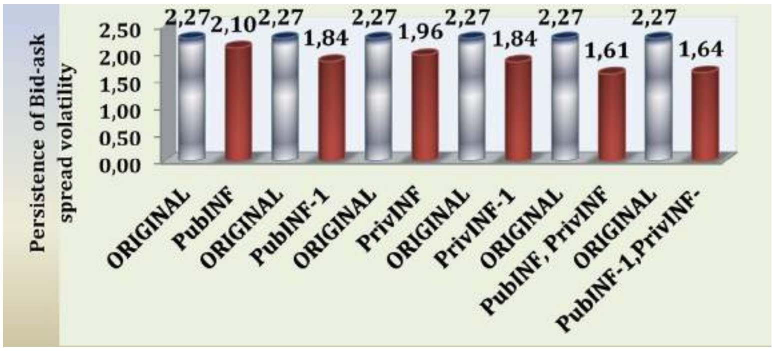

Fig. 1. The effect of the information flow on the persistence of depth at best limit.

in contemporaneous order imbalance leads to a reduction in liquidity risk for 29% of the sample. Consequently, private information flow in the Tunisian market generates an ambiguous relationship between order imbalance and liquidity risk. Second, the lagged order imbalance coefficient $P(rivINF_{t,i-1})$ appears significant and positive in 18 cases (48%), significant and negative in 12 cases (32%), non-significant and positive in three cases (8%), and non-significant and negative for the remaining five cases (13%). This empirical evidence verifies the existence of a lagged positive relationship between order imbalance and bid-ask spread volatility for 47% of our sample.

Panel B in Table 5 presents the empirical findings of depth at best limit volatility specified by Eqs (13) and (14). First, the private information coefficient ($PrivINF_{t,i}$) is strictly positive and significant in 25 cases (66%) and significant and negative in 10 cases (26%), whereas it is non-significant and negative in two cases (5%) and non-significant and positive in one case (2%). The relationship between trading volume and liquidity risk is almost clear for the Tunisian market because an increase in the contemporaneous order imbalance enhances the depth at best limit volatility for 66% of our sample and, therefore, there is an increase in liquidity risk. Second, the lagged trading volume coefficient ($PrivINF_{t,i-1}$)is strictly positive and significant in 19 cases (50%), and significant and negative in 11 cases (29%). However, it is non-significant and positive in four cases (10%) and non-significant and negative in four cases (10%). Based on this result, the relationship between lagged order imbalance and liquidity risk is ambiguous for the TSM.

4.3.3. *The case of public–private information flow*

Panel C in Table 4 illustrates the results of regressions 15 and 16. First, the contemporaneous order imbalance coefficient ($PrivINF_{t,i}$) appears significant and positive in 12 cases (32%) and significant and negative in 15 cases (40%), whereas it is non-significant and positive in six cases (16%) and non-significant and negative in five cases (13%). The increase in the contemporaneous order imbalance because of private information flow increases the liquidity risk for 32% of the sample. The trading volume coefficient ($PubINF_{t,i}$) is significant and positive in 16 cases (42%) and significant and negative in 16 cases (42%); however, it is non-significant and positive in three cases (8%) and non-significant and negative in three cases (8%). Therefore, an increase in contemporaneous trading volume augments the bid-ask spread volatility and aggravates liquidity risk for 42% of the entire sample. Our results show that the arrival of both contemporaneous private and contemporaneous public information did not have a clear effect on liquidity risk. Second, our empirical results report that the lagged order imbalance coefficient ($PrivINF_{t,i-1}$) appears strictly significant and positive in 13 cases (34%) and significant and negative in seven cases (19%), whereas it is non-significant and positive in 11 cases (29%) and non-significant and negative in seven cases (19%). The lagged trading volume coefficient ($PubINF_{t,i-1}$) is significant and positive in 23 cases (60%) and significant and negative in 13 cases (34%). However, it is non-significant and positive in one case (3%) and non-significant and negative in one case (3%). This empirical evidence shows that the lagged relationship between order imbalance and bid-ask spread volatility is ambiguous. For the lagged trading volume, the increase in this variable generates an increase in liquidity risk for 61% of the sample. We deduced that the trading volume dominates the order imbalance in the deterioration of liquidity risk for a large portion of the shares in the TSM. Consequently, public information arrival dominates private information arrival with respect to the liquidity risk effect in the TSM.

Fig. 1 shows the impact of information flow on the persistence of bid-ask spread volatility. In Fig. 1, the average degree of persistence decreases from 2.27 in the case of the original ARCH model to 2.10 for contemporaneous trading volume, 1.84 for lagged trading volume, 1.96 for contemporaneous order imbalance, 1.84 for lagged order imbalance, 1.61 for the simultaneous arrival of contemporaneous trading volume and the contemporaneous order imbalance, and 1.64 for the simultaneous arrival of the lagged trading volume and the lagged order imbalance. Our findings explain the role of information variables in the persistence of liquidity risk associated with the bid-ask spread for most cases. However, a decrease in the degree of persistence occurred mainly with the simultaneous arrival of past private and public information. Hence, we confirm that information flow in the TSM decreases the persistence of liquidity risk.

Panel C in Table 5 presents the estimation results for the depth at best limit volatility specified in equations 15 and 16. First, the contemporaneous trading volume coefficient ($PubINF_{t,i}$) is strictly positive and significant in 10 cases (27%) and

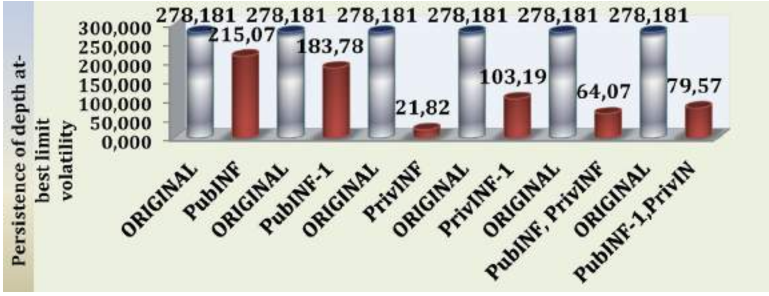

Fig. 2. Effect of the information flow on the persistence of the depth at-best limit.

significant and negative in 27 cases (71%), whereas the coefficient is non-significant and negative in one case (2%). The contemporaneous order imbalance coefficient ($PrivINF_{t,i}$) is significant and positive in 15 cases (40%) and significant and negative in nine cases (24%), whereas it is non-significant and positive in five cases (13%) and non-significant and negative in nine cases (24%). Therefore, the contemporaneous relationship between order imbalance and depth at best limit volatility is ambiguous. However, an increase in the contemporaneous trading volume ($PubINF_{t,i}$) contributes to liquidity risk diminution in the TSM (verified for 71% of our sample).

From this result, we interpret that the trading volume dominates the order imbalance in the reduction of liquidity risk for a large portion of securities in the Tunisian market.

Second, the empirical evidence shows that the lagged trading volume coefficient ($PubINF_{t,i-1}$) is strictly positive and significant in 16 cases (42%) and significant and negative in 20 cases (53%). However, it is non-significant and negative in one case (2%) and non-significant and positive in one case (2%). The lagged imbalance order coefficient $P(rivINF_{t,i-1}$) is significant and positive in 12 cases (31%) and significant and negative in seven cases (19%); whereas it is non-significant and positive in 11 cases (29%) and non- significant and negative in eight cases (21%). This empirical evidence shows that the lagged relationship between order imbalance and depth at best limit volatility and between trading volume and depth at best limit are clear. We deduce that the lagged trading volume dominates the order imbalance in the reduction of liquidity risk for 53% of the shares on the Tunisian market.

Fig. 2 reveals the effect of information flow on persistence of depth at best limit volatility. It is clear from Fig. 2 that the average degree of persistence has reduced, on average, from 278.181 in the case of the original ARCH models to 215.07 for contemporaneous trading volume and to 183.78 for lagged trading volume. These results imply that the volatility of this variable is explained by passed volatility that persists over time. The results indicate that the lagged trading volume and the contemporaneous trading volume is unable to fully explain the GARCH effect in the series for depth at best limit for the majority of TSM cases. However, the persistence has decreased substantially to 21.82 for contemporaneous order imbalance, 103.19 for lagged order imbalance, 64.07 for the simultaneous arrival of contemporaneous trading volume and contemporaneous order imbalance, and 79.57 for the simultaneous arrival of lagged trading volume and lagged order imbalance. Thus, we confirm that the persistence of the GARCH effect for depth at best limit series vanishes and almost disappears for contemporaneous private information and the simultaneous flow of contemporaneous public and private information.

5. Conclusion

This paper examines the effect of information flow on liquidity and liquidity risk in an emerging stock market. We use an econometric approach based time series regression such ARMA and various GARCH family models to account for the phenomenon of asymmetry. We use a database that contains intraday observations from the TSM during the period October 2008 to June 2009. Our analysis highlights many findings. First, for major Tunisian stocks, both public and private information flows are dominant factors in liquidity improvements in the TSM. Liquidity improvement is generated by a decrease in the bid-ask spread accompanied by an increase in the depth at best limit. Second, our findings clearly indicate that the arrival of public information in a sequential manner is the dominant factor generating an increase in liquidity risk related to the bid-ask spread. The arrival of contemporaneous private information arrival is the dominant factor generating an increase in liquidity risk related to the depth at best limit. Third, our results show that liquidity risk persistence disappears when both contemporaneous private and public information arrive on the TSM. Finally, our analysis has implications for future research. An alternative approach founded on the multivariate GARCH-type processes could be applied to verify and improve the findings determined from the application of the uni-variate ARCH models.

Our results have useful implication both in terms of academics, regulators and investors. First, the study of the liquidity-information flow relationship on emerging stock market is important in order to understand the process of liquidity formation. This point is very important for investors in terms of portfolio diversification. Second, knowing the factors affecting liquidity leads to high confidence level among investors in order to understand the market dynamic. Loosely speaking, learning the effect of lagged information spillover on the liquidity in TSM allows investors to exploit this kind of information to make expectation. Third, the liquidity deterioration is a symptom of adverse selection problem. To avoid such problem,

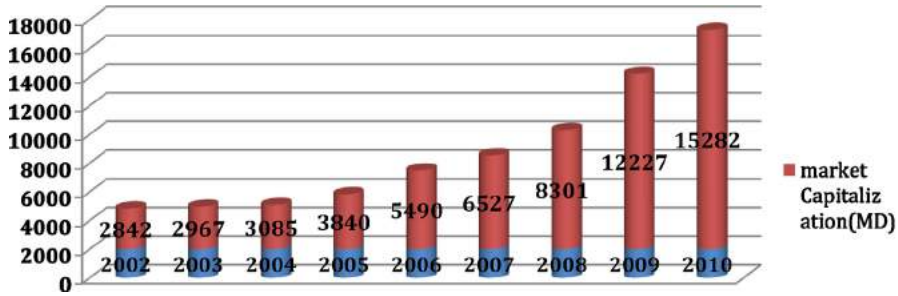

Fig. A.1. The evolution of the capitalization market in Tunisian stock market from 2002 to 2010.

the financial authorities and regulators can promulgate legislation in order to avoid liquidity sudden evaporation and avoid insider trading.

Appendix A. Appendix A

Fig. A.1
Table A.1
Table A.2
Table A.3
Table A.4

Appendix B. Appendix B

In our analysis we proceed to estimate various GARCH specification in order to select the optimal models, representing our data. The method of identification is based on time series analysis principal. Here, we present all estimated specifications:

- ARCH (p) process of Engle (1982)

The basic idea advanced by Engle is based on the non-constancy of volatility over time. He confirmed the dependence of the volatility to the information we have. The equation of the conditional variance ARCH (p)[11] depends essentially on the explanatory power of the squared error terms of p past periods. In this case, the ARCH specification can be written as follows:

$$h_t^2 = \alpha_0 + \sum_{i=1}^{p} \alpha_i \varepsilon_{t-1}^2 + \varepsilon_t$$

- GARCH (p, q) process of Bollerslev (1986)

Bollerslev (1986) developed a generalized autoregressive conditional heteroscedastic model (GARCH model). Through this model, it tried to discover a solution to account for the presence of long memory in volatility and especially not to fall into the violation of the non-negativity constraint of the variance. This specification of the conditional variance equation requires less parameter to be estimated that the formulation ARCH (p) in order to model the phenomena of persistence of volatility shocks. GARCH process is determined by the squared error terms of p past periods and lagged conditional variances of q past periods. This structure has the advantage of being more parsimonious because it is composed by a minority of parameters compared to ARCH model having many parameters to estimate. The equation of the conditional variance in the GARCH process can be formulated as follows:

$$h_t^2 = \alpha_0 + \sum_{i=1}^{p} \alpha_i \varepsilon_{t-1}^2 + \sum_{j=1}^{q} \beta_j \sigma_{t-j}^2 + \varepsilon_t$$

where $\alpha_0 \geq 0$, α_i and $\beta_j \geq 0$.

- EGARCH (p, q) process of Nelson (1991)

The EGARCH model (or the Exponential GARCH model), proposed by Nelson (1991), takes into account the impact of good news and bad news, or a positive and negative shock on the conditional variance. But it should be noted that the two

[11] The variance of the error term at time t.

Table A.1
Summary statistics of stocks liquidity variables, trading volume and order imbalance.

STOCKS	Quoted spread					depth-at-best-limit					Trading volume					Order imbalance				
	Mean	SD	Skewn	Kurt	J-B	Mean	SD	kewn	Kurt	JB	Mean	SD	Skewn	Kurt	J-B	Mean	SD	kewn	Kurt	JB
ADWYA	−0.1	0.2	−2	106	1,957,255	4.4	2.6	−1	2.15	442	3.1	3.4	0.4	1.43	562	−0.4	4	−3	105	190,523
AMEN BANK	−0.2	1	4.8	361	235,329	2.3	2.4	0.4	1.65	433	1.6	2.5	1.2	2.71	1006	0	1.9	−0	34.2	179,671
ARTES	−0.1	0.2	−4	38	236,667	4.2	2.6	−0	2.09	306	3	3.3	0.4	1.58	498	−0.7	3.9	1.2	92.6	147,737
ASSAD	−0.1	0.6	32	1660	506,000	4.3	2.3	−1	2.65	483	3.5	3.2	0	1.39	480	−0.9	3.6	−2	47.6	367,889
ATB	−0.1	0.2	−5	121	257,022	3.4	2.7	−0	1.56	400	2.2	3	0.8	1.88	642	−0.3	2	−4	89.9	140,472
ATL	−0	0.1	−11	258	120,520	4.3	2.8	−1	1.96	440	3.1	3.4	0.4	1.45	558	−0.8	3.1	−2	37.7	224,498
Attijari Bank	−0.1	0.3	−6	70.1	857,416	4.2	2.4	−1	2.37	413	3.3	3.2	0.1	1.38	493	−0.2	3.7	1.2	77.8	102,925
BH	−0.2	0.6	−5	128	290,114	3	2.5	0.1	1.71	308	2.1	2.8	0.9	2.31	701	−0.4	2.5	−4	69.2	819,358
BIAT	−0.4	0.8	−3	19.3	54,155	2.1	2.5	0.6	1.83	508	1.2	2.3	1.7	4.34	2393	−0	1.7	6.9	175	545,720
BNA	−0.1	0.2	−1	14.7	26,225	3.4	2.9	−0	1.48	427	2.2	3.2	0.9	2.13	728	0.1	2.8	2.9	62	646,309
BT	−0.6	2.5	5.2	216	839,702	2.9	2	−0	1.95	219	2.4	2.7	0.5	1.7	479	−0.2	3.9	2.8	69.8	826,076
BTE-ADP	−0.2	1	15	278	140,624	1.1	1.9	1.4	3.41	1437	0.6	1.5	2.7	8.84	11,493	0	0.8	0.9	71	851,665
CIL	−0.1	0.6	7.5	349	220,229	2.9	2.5	−0	1.44	449	1.8	2.7	1	2.23	791	−0.4	1.9	−2	25.1	93,693
EL WIFACK Leasing	−0.1	0.3	−11	258	120,885	2.3	2.7	0.6	1.72	522	1.2	2.4	1.8	4.68	2893	−0.1	1	−2	30.6	141,815
ELECTROSTAR	−0.2	0.8	55	3443	218,000	1.7	2.4	0.8	2.01	654	0.9	2.1	2	5.28	3812	−0	1.3	0.2	45.7	336,147
ESSOUKNA	−0.1	0.1	−2	9.47	10,369	1.4	2.3	1.3	2.99	1153	0.6	1.7	2.8	9.67	14,038	0	1	8.9	301	163,754
GIF	−0.1	0.1	−7	78.8	109,098	3	2.9	0.2	1.38	504	1.7	2.9	1.3	3.05	1243	0	2.3	5.4	101	177,917
Magasin General	−0.7	1.6	−3	19.6	57,815	1.7	2.1	0.7	2.11	501	1	2	1.7	4.46	2528	0.1	1.8	0.9	56	517,340
MONOPRIX	−1.4	2.6	−4	29	135,321	1.6	1.9	0.7	2.19	518	0.8	1.7	1.9	5.19	3481	−0.1	1.3	−2	33.1	169,764
POULINAGROUP	−0.1	0.2	−5	105	193,758	4.9	2.5	−1	2.77	355	3.6	3.6	0.3	1.52	461	−1.2	7.6	−6	129	296,639
SFBT	0.1	3.8	27	729	975,799	3.5	2.8	−0	1.55	394	2.2	3.1	0.8	2	687	−0.4	2.2	−2	31.5	151,506
SIAME	−0	0.1	−13	304	167,876	2.8	3.1	0.4	1.41	560	1.6	2.9	1.5	3.43	1598	−0.3	1.8	4.1	179	572,549
SIMPAR	−0.5	0.9	−3	15	32,587	1	1.9	1.5	3.95	1837	0.5	1.5	3	11.1	18,891	−0.1	0.7	−2	48.1	378,402
SIPHAT	−0.3	0.4	−2	8.79	8546	1.6	2.2	1	2.49	734	0.7	1.8	2.5	7.79	8663	−0.1	1	−3	46.3	349,301
SITS	−0	0.1	−6	160	456,275	3.5	3.2	0	1.31	524	2.4	3.5	0.9	2.16	769	0.1	3.7	5.4	102	1,840,851
SOMOCER	−0	0.1	−1	36.8	211,283	4.9	2.6	−1	2.6	595	3.4	3.6	0.3	1.38	533	−1.1	3.6	−1	43.3	300,100
SOTETEL	−0.2	0.4	−3	19	54,257	2.8	2.4	−0	1.51	411	1.8	2.6	1	2.41	826	−0.5	3	5.5	243	106,383
SOTRAPIL	−0.2	0.4	−6	51.8	463,759	2.2	2.3	0.3	1.59	454	1.3	2.3	1.4	3.39	1453	−0.3	1.7	1.4	92.2	1,464,971
SOTUMAG	−0	0	−2	9.74	10,989	1.2	2.4	1.6	4.02	2180	0.6	1.9	3.1	11.1	19,021	−0.1	0.7	−5	73.6	937,862
SOTUVER	−0.4	1	5.5	267	128,085	1.1	2	1.5	4	1884	0.9	2.1	2.2	6.71	6215	0.3	2.2	6.2	104	1,907,938
SPDIT-SICAF	−0.1	0.2	13	596	648,835	2.1	2.8	0.8	2.06	628	1	2.4	2.1	5.79	4532	−0.1	1.6	−22	951	166,000
STAR	−1	2	−4	39.7	258,782	2.5	2	−0	1.76	285	1.7	2.4	0.9	2.33	711	−0.1	3.3	7.5	230	948,868
STB	−0.1	0.2	−4	36.2	216,322	3.4	2.9	−0	1.5	414	2.2	3.2	0.9	2.24	744	−0.2	2.7	1.5	42.6	289,965
TPR	−0	0.1	8	267	128,355	5.2	2.2	−1	3.81	974	4.6	3.4	−0	1.61	433	−1.4	5	−4	50.1	421,870
TUNINVEST-SICAR	−0.2	0.6	−13	227	938,929	2	2.5	0.6	1.73	557	1.1	2.3	1.7	4.27	2410	−0	1.6	4.4	80.6	112,287
TUNISAIR	−0	0.2	−8	108	206,342	4.5	2.8	−1	2.06	427	3.1	3.5	0.4	1.5	544	−0.9	3.3	−2	42.9	294,606
TUNISIE LEASING	−0.1	0.4	−3	207	766,821	3.6	2.3	−0	2.04	263	2.7	2.9	0.4	1.61	493	−0.7	3.2	−5	103	184,701
UIB	−0.1	0.3	−7	70.4	869,096	3.2	2.7	−0	1.44	450	2.1	2.9	0.8	1.93	708	−0.3	1.8	−3	29.7	137,193

Table A.2
Unit root test for intraday quoted spread, intraday depth-at-best-limit, intraday trading volume and intraday order imbalance data for 38 stocks.

STOCKS	Intraday trading volume						Intraday order imbalance						Intraday spread						Intraday depth-at-best-limit					
	ADF			PP			ADF			PP			ADF			PP			ADF			PP		
	C-T	*C*	NONE	C-T	*C*	NONE	C-T	*C*	NONE	C-T	*C*	NONE	C-T	*C*	NONE	C-T	*C*	NONE	C-T	*C*	NONE	C-T	*C*	NONE
ADWYA	−20.8			−49			−60.9			−60.92			−22.2	−22.2		−32.25			−23			−5322		
AMENBANK	−38.9			−49.73			−62.5			−62.57			−19.4	−19.4		−32.24	−32.2		−24.3			−5401		
ARTES	−23.7	−23.7		−47.64	−47.6		−41.3			−62.69			−24.8	−24.8		−39.23	−39.2		−20.2	−20.2		−5391	−53.9	
ASSAD	−16.2	−16.2		−51.79	−51.8		−57.6			−57.74			−25.2	−25.2		−55.6	−55.6		−23.3	−23.3		−5197	−52	
ATB	−20.2			−53.88			−57.6			−57.59			−26.5	−26.5		−37.32	−37.3		−23.3			−5601		
ATL	−18.5			−50.51			−40.1			−56.37			−34.3			−41.61			−19.7			−5355		
Attijari Bank	−22.6			−63.4			−31.8			−58.68			−24.9			−29.03			−23	−23		−5129	−51.3	
BH	−35.2			−51.3			−42.6			−60.43			−26.7			−37.58			−23.5			−52.7		
BIAT	−28.1			−54.08			−60.5			−60.42			−19.2			−25.72			−22.1			−5541		
BNA	−17.6			−49.65			−18			−60.02			−20			−29.71			−15.9			−5544		
BT	−15.3			−48.61			−61.2			−61.21			−23.8	−23.8		−36.09			−16.6			−5352		
BTE-ADP	−28.7			−57.73			−63.7	−63.7		−63.71	−63.7		−15.5	−15.5		−15.64	−15.6		−25.7			−5663		
CIL	−23.3			−52.36			−59.3			−59.5			−31.8	−31.8		−31.34	−31.3		−21.7			−5369		
ELECTROSTAR	−22.2	−22.2		−54.01	−54		−41.9	−41.9		−60.29	−60.3		−23.4	−23.4		−61.05	−61.1		−23.1	−23.1		−5502	−55	
ELWIFACKLEASING	−22			−50.43			−43.3			−62.96			−27.7			−28.16			−21.1	−21.1		−5113	−51.1	
ESSOUKNA	−24.8	−24.8		−54.93	−54.9		−62.3			−62.34			−16.1	−16.1		−18.02	−18		−23.3	−23.3		−5506	−55.1	
GIF	−17.1			−50.97			−27.4			−55.63			−18.2			−23.1			−18.7			−5297		
Magasin General	−20.6			−52.87			−58.5	−58.3		−58.47	−58.3		−22.1	−22.1		−24.59	−24.6		−19.3			−5221		
MONOPRIX	−24.1	−24		−53.49			−63.8			−63.82			−19.1			−24.48			−19.1			−5626		
POULINAGROUP	−39.2			−49.56			−64.4	−64.3		−64.35	−64.3		−23.7			−37.91			−24.5	−24.4		−53.5		
SFBT	−27.3			−55.37			−60.2			−60.21			−21	−21	−2101	−20.67	−20.7	−2067	−24.2			−5503		
SIAME	−24.1	−24.1		−50.45	−50.5		−61.1	−61.1		−61.11	−61.1		−24.4	−24.4		−25.72	−25.7		−17.6	−17.6		−5294	−52.9	
SIMPAR	−24.1			−56.32			−59.1			−59.09			−15.9			−18.03			−23.5			−5627		
SIPHAT	−19.7	−19.7		−51.46	−51.5		−39.7	−39.7		−55.39	−55.4		−22	−22		−23.94	−23.9		−20.2	−20.2		−5477	−54.8	
SITS	−17			−48.66			−31.6			−57.57			−30.4			−34.98			−13.8			−5492		
SOMOCER	−21.9	−21.9		−50.47			−40	−39.9		−57.81	−57.8		−24.9			−43.19			−24			−5547		
SOTETEL	−20.9			−51.42			−62.7			−62.72			−27.2	−27.2		−30.25	−30.3		−20.4			−54		
SOTRAPIL	−20.8	−20.8		−52.91	−52.9		−64.3			−64.29			−21.5	−21.5		−28.35	−28.3		−18.7			−5468		
SOTUMAG	−37.2			−51.74			−61	−60.8		−60.99	−60.8		−16.5	−16.5		−17.38	−17.4		−34.3			−5918		
SOTUVER	−15.4	−14.1		−45.6	−43.7		−31.9			−56.96			−24.6	−24.6		−35.62	−35.6		−12.7	−11.3		−4357	−40.4	
SPDIT-SICAF	−22.9			−53.7			−60.1	−60.1		−60.1	−60.1		−19.4			−39.85			−20.2			−5502		
STAR	−17.9			−47.92			−33.8			−59.04			−29.2			−34.94			−16.8			−5135		
STB	−16.3			−50.66			−26.5			−62.87			−25.7			−28.9			−18.9			−5327		
TPR	−18.1			−49.21			−26.8	−26.7		−57.38			−40.7	−40.7		−54.6	−54.6		−19.4			−5344		
TUNINVEST-SICAR	−22.7			−50.23			−30.7			−53.85			−16.9	−16.9		−17.32	−17.3		−19.1			−5398		
TUNISAIR	−22.4			−50.96			−40.2			−58.42			−25.1			−29.86			−18.6			−5548		
TUNISIE LEASING	−19.9			−50.07			−55.9			−55.94			−26.5	−26.6		−49.92	−49.9		−23.8			−5393		
UIB	−25.7			−52.95			−57.7			−57.8			−23.4	−23.3		−26.05	−26		−25.7	−25.6		−5444	−54.4	

Notes: C-T corresponds to the regression including a constant term and a linear trend. *C* implies that regression contains only a constant term, and none traduce the model without trend and constant terms. The critical values respectively at 1%, 5% and 10% are −3.9726, −3.4189 and −3.1304. *C* corresponds to the regression including a constant term only. The critical values respectively at 1%, 5% and 10% are 3.4399, −2.8650 and −2.5686.

Table A.3
Diagnostic tests for the selected ARMA(p, q) models.

TITRE	Intraday spread								Intraday depth at best limit							
	Equation	AIC	SIC	Ljung–Box pierce test			Test LM-Arch		Equation	AIC	SIC	Ljung–Box pierce test			Test LM-Arch	
				Q(5)	Prop	p	Valeurs	Prop				Q(5)	Prop	p	Valeurs	Prop
ADWYA	MA(7)	−1.241	−1.229	6.797	1.000	1	270,544	0.0000*	ARMA(4.8)	4.65	4.67	1.944	1.000	1	9,342,173	0.0022*
AMENBANK	ARMA(2.2)	2.351	2.358	1.189	0.756	5	163,187	0.0000*	ARMA(2.1)	4.2	4.2	54.379	0.000	4	4,356,928	0.0000*
ARTES	ARMA(2.2)	−0.427	−0.42	0.441	0.932	1	305,079	0.0000*	ARMA(8.8)	4.64	4.66	9.391	0.669	9	1,493,003	0.0929***
ASSAD	ARMA(2.2)	1.71	1.717	3.383	0.000	1	3.65	0.0561**	ARMA(1.1)	4.38	4.39	0.58	0.446	4	1,124,652	0.0105**
ATB	ARMA(2.5)	−1.095	−1.084	0.046	1.000	2	651,455	0.0000*	AR(4)	4.75	4.75	10.144	0.181	2	1,614,248	0.0003*
ATL	ARMA(1.2)	−1.438	−1.432	0.892	0.827	4	4083	0.0000*	ARMA(5.9)	4.72	4.74	0.124	1.000	0	0.143649	0.7047
Attijari Bank	ARMA(1.3)	−0.455	−0.448	6.1	0.047	3	685,498	0.0000*	ARMA(2.1)	4.45	4.46	5.854	0.119	1	2,847,733	0.0000*
BH	ARMA(2.2)	1.534	1.542	0.041	0.998	4	690,738	0.0000*	AR(4)	4.61	4.61	5.068	0.652	2	2,283,474	0.0000*
BIAT	ARMA(2.6)	1.563	1.576	0.278	1.000	4	364,184	0.0000*	ARMA(1.1)	4.57	4.59	4.44	0.350	1	7,945,881	0.0048*
BNA	ARMA(3.5)	−1.211	−1.198	0.212	1.000	3	218,346	0.0000*	ARMA(1212)	4.83	4.87	40.803	0.000	7	5,723,434	0.0000*
BT	ARMA(3.5)	4.312	4.325	0.106	1.000	1	282,011	0.0000*	ARMA(6.6)	4.07	4.09	5.114	1.000	1	4,336,266	0.0373**
BTE-ADP	ARMA(1.10)	1.009	1.027	0.878	1.000	0	0.272	0.6022	ARMA(1.1)	4.13	4.13	1.739	0.628	3	6,578,058	0.0000*
CIL	ARMA(1.4)	1.246	1.255	0.72	0.396	5	15,315	0.0000*	AR(5)	4.58	4.59	25.425	0.147	4	2,678,997	0.0001*
ELECTROSTAR	ARMA(2.2)	2.443	2.451	2.775	0.000	1	374,976	0.0000*	ARMA(1.1)	4.48	4.48	2.552	0.635	0	1,266,837	0.2604
ELWIFACKLEASING	ARMA(1.3)	−0.706	−0.699	0.021	0.989	3	121,533	0.0000*	ARMA(2.2)	4.67	4.68	4.041	0.257	1	2,348,863	0.0000*
ESSOUKNA	ARMA(2.5)	−2.675	−2.664	0.058	1.000	4	132,398	0.0000*	AR(2)	4.42	4.43	39.805	0.000	6	1,248,157	0.0000*
GIF	ARMA(2.10)	−2.184	−2.165	0.027	1.000	3	884,947	0.0000*	AR(5)	4.84	4.85	4.306	0.366	5	7,528,875	0.0000*
Magasin General	ARMA(1.9)	2.919	2.935	0.012	1.000	3	637,225	0.0000*	AR(5)	4.18	4.19	1.132	0.769	4	4,648,782	0.0000*
MONOPRIX	ARMA(1.2)	3.912	3.92	1.915	0.590	1	50,159	0.0000*	ARMA(6.5)	4.02	4.04	8737	0.033	1	1,726,867	0.0000*
POULINAGROUP	ARMA(4.4)	−0.688	−0.675	0.161	0.688	3	222,725	0.0000*	ARMA(4.3)	4.6	4.61	11.807	0.003	3	1,843,455	0.0004*
SFBT	ARMA(1.1)	4.318	4.323	0.177	1.000	0	18,265	0.0000*	AR(4)	4.86	4.87	37.682	0.010	1	106,483	0.0011*
SIAME	ARMA(2.5)	−2.991	−2.979	0.321	1.000	6	115,762	0.0000*	AR(6)	4.98	4.99	25.748	0.137	5	8,348,266	0.0000*
SIMPAR	ARMA(3.4)	1.255	1.267	0.101	0.751	4	101,285	0.0000*	ARMA(1.1)	4.04	4.04	0.549	1.000	6	1,453,817	0.0000*
SIPHAT	ARMA(1.3)	0.023	0.03	5.448	0.066	2	173,156	0.0000*	ARMA(2.2)	4.3	4.31	0.478	0.924	1	975,272	0.0018*
SITS	ARMA(1.2)	−3.041	−3.035	4.463	0.216	4	734,477	0.0000*	ARMA(2.2)	4.92	4.92	20.343	0.314	2	4,463,031	0.0000*
SOMOCER	ARMA(2.2)	−2.434	−2.426	1.881	0.598	3	683,081	0.0000*	ARMA(2.2)	4.7	4.71	5.887	0.117	4	6,743,166	0.0000*
SOTETEL	AR(1)	0.297	0.3	1.922	0.860	2	250,418	0.0000*	AR(5)	4.44	4.45	41.273	0.003	1	3,696,634	0.0000*
SOTRAPIL	ARMA(3.7)	0.498	0.514	0.035	1.000	3	508,999	0.0000*	AR(3)	4.42	4.43	7.096	0.131	2	2,237,573	0.0000*
SOTUMAG	ARMA(1.1)	−5.07	−5.065	4.37	0.358	4	42,731	0.0000*	ARMA(1.1)	4.6	4.61	2.306	0.316	5	7,582,392	0.0000*
SOTUVER	ARMA(3.6)	2.408	2.422	0.023	1.000	2	101,269	0.0000*	ARMA(2.2)	3.7	3.71	0.927	1.000	10	5,979,268	0.0000*
SPDIT-SICAF	ARMA(1.1)	−0.894	−0.89	1.556	0.817	3	111,624	0.0000*	ARMA(1.1)	4.78	4.79	0.088	1.000	1	7,530,916	0.0061*
STAR	ARMA(1.4)	3.79	3.799	0.925	0.336	3	468,086	0.0000*	ARMA(2.2)	3.79	3.8	2.645	0.450	1	1,199,725	0.0005*
STB	ARMA(1.4)	−0.931	−0.922	1.031	0.310	4	179,111	0.0000*	MA(3)	4.89	4.9	12.499	0.000	2	7,797,858	0.0203*
TPR	AR(1)	−1.195	−1.192	2.445	0.485	1	62,924	0.0000*	ARMA(5.6)	4.3	4.31	0.092	1.000	5	1,187,727	0.0000*
TUNINVEST-SICAR	ARMA(1.10)	0.299	0.317	0.225	1.000	0	1514	0.2185	AR(6)	4.53	4.54	15.793	0.201	4	8,693,286	0.0000*
TUNISAIR	ARMA(1.3)	−1.554	−1.547	1.614	0.446	5	444,394	0.0000*	ARMA(6.8)	4.79	4.81	0.012	1.000	1	6,442,591	0.0111**
TUNISIE LEASING	ARMA(1.1)	1.114	1.118	5.66	0.226	9	167,918	0.0000*	ARMA(1.4)	4.45	4.45	0.14	0.709	1	3,680,981	0.0000*
UIB	ARMA(1.7)	−0.246	−0.233	0.081	1.000	1	28,571	0.0000*	ARMA(1.4)	4.73	4.74	6.111	0.013	5	3,280,697	0.0000*

Notes: $Q(5)$ is the Ljung–Box portmanteau statistics to test the null of no serial correlation up to lag 5 for the return series. LM(k) is the Lagrange multiplier test up to lag k.

Table A.4
Results of intraday quoted spread and intraday depth modeling through various GARCH family models.

STOCKS	Univariate ARCH specification	Bid-ask spread				$\alpha_1+\beta_1+1/2\gamma_1$	Univariate ARCH specification	Depth at-best limit				$\alpha_1+\beta_1+1/2\gamma_1$
		α_1	γ_1	β_1	δ_1			α_1	γ_1	β_1	δ_1	
ADWYA	GJR-GARCH(1.1)	0.333	−0.245	0.717		0.927	TGARCH(1.1)	0.408	−0.44	0.832		1.02
		0.0000*	0.0000*	0.0000*				0.00*	0.00*	0.00*		
AMENBANK	EGARCH(1.1)	1.767	0.169	0.784		2.635	TGARCH(1.1)	0.037	0.297	0.539		0.725
		0.0000*	0.0000*	0.0000*				0.177	0.00*	0.00*		
ARTES	PGARCH(1.1)	0.541	−0.299	0.309	0.353	0.7	TGARCH(1.1)	0.1	−0.105	0.948		0.996
		0.0000*	0.0000*	0.0000*	0.0000*			0.00*	0.00*	0.00*		
ASSAD	PGARCH(1.1)	0.881	−0.328	0.176	0.481	0.893	EGARCH(1.1)	0.417	0.109	0.72		1.191
		0.0000*	0.0000*	0.0000*	0.0000*			0.00*	0.00*	0.00*		
ATB	PGARCH(1.1)	0.799	−0.39	0.278	0.569	0.882	GARCH(1.1)	0.015		0.97		0.986
		0.0000*	0.0000*	0.0000*	0.0000*			0.153		0.00*		
ATL	EGARCH(1.1)	1.63	0.449	0.674		2.528	TGARCH(1.1)	0.39	−0.43	0.79		0.964
		0.0000*	0.0000*	0.0000*				0.00*	0.00*	0.00*		
Attijari Bank	PGARCH(1.1)	0.666	−0.323	0.242	0.515	0.746	TGARCH(1.1)	0.302	−0.386	0.386		0.496
		0.0000*	0.0000*	0.0000*	0.0000*			0.00*	0.00*	0.00*		
BH	PGARCH(1.1)	0.73	−0.259	0.332	0.56	0.933	GARCH(1.1)	0.046		0.732		0.778
		0.0000*	0.0000*	0.0000*	0.0000*			0.08***		0.00*		
BIAT	EGARCH(1.1)	1.767	0.066	0.641		2.441	GJR-GARCH(1.1)	0.078	0.996	0.309		0.884
		0.0000*	0.0000*	0.0000*				0.981	0.981	0.01**		
BNA	EGARCH(1.1)	1.697	0.204	0.687		2.486	TGARCH(1.1)	0.031	0.021	0.932		0.974
		0.0000*	0.0000*	0.0000*				0.04**	0.225	0.00*		
BT	PGARCH(1.1)	0.608	−0.353	0.346	0.237	0.777	TGARCH(1.1)	0.01**	0	0.987		0.998
		0.0000*	0.0000*	0.0000*	0.0000*			0.00*	0.933	0.00*		
BTE-ADP	GJR-GARCH(1.1)	6.851	−0.175	0.031		6.794	PGARCH(1.1)	0.385	0.968	0.09**	0.074	0.964
		0.0000*	0.0000*	0.0000*				0.00*	0.00*	0.00*	0.00*	
CIL	PGARCH(1.1)	0.713	−0.373	0.348	0.08	0.875	TGARCH(1.1)	0.01**	0.01*	0.967		0.986
		0.0000*	0.0000*	0.0000*	0.0000*			0.324	0.522	0.00*		
ELECTROSTAR	EGARCH(1.1)	1.067	0.091	0.789		1.901	TGARCH(1.1)	1.095	8832.85	0		441.752
		0.0000*	0.0000*	0.0000*				0.00*	0.00*	0.00*		
ELWIFACKLEASING	EGARCH(1.1)	1.08	0.238	0.808		2.006	TGARCH(1.1)	0.404	36.345	0.281		18.857
		0.0000*	0.0000*	0.0000*				0.00*	0.00*	0.00*		
ESSOUKNA	GJR-GARCH(1.1)	12.308	−0.101	0		12.257	EGARCH(1.1)	3.413	−2.298	0.722		2986
		0.0000*	0.0000*	0.0001*				0.00*	0.00*	0.00*		
GIF	EGARCH(1.1)	1.52	0.193	0.694		2311	GJR-GARCH(1.1)	0.076	0.992	0.776		1.348
		0.0000*	0.0000*	0.0000*				0.946	0.946	0.00*		
Magasin General	EGARCH(1.1)	1.317	0.087	0.656		2.016	TGARCH(1.1)	0.996	51.352	0.053		26.725
		0.0000*	0.0000*	0.0000*				0.00*	0.00*	0.00*		
MONOPRIX	EGARCH(1.1)	1.11	0.173	0.776		1.972	GJR-GARCH(1.1)	0.248	0.999	0.789		1.537
		0.0000*	0.0000*	0.0000*				0.91	0.91	0.00*		
POULINA	EGARCH(1.1)	1.361	0.173	0.849		2297	PGARCH(1.1)	0.101	−1	0.568	0.447	0.17

Table A.4 (*Continued*)

STOCKS	Univariate ARCH specification	Bid-ask spread α_1	γ_1	β_1	δ_1	$\alpha_1+\beta_1+1/2\gamma_1$	Univariate ARCH specification	Depth at-best limit α_1	γ_1	β_1	δ_1	$\alpha_1+\beta_1+1/2\gamma_1$
		0.0000*	0.0000*	0.0000*				0.00*	0.00*	0.00*	0.00*	
SFBT	PGARCH(1.1)	4.137	−0.088	3354	0.006	7.447	GARCH(1.1)	0.012		0.979		0.991
		0.0000*	0.0000*	0.0000*	0.0103			0.206		0.00*		
SIAME	EGARCH(1.1)	1.388	0.245	0.719		2.229	TGARCH(1.1)	0.699	23.911	0.106		1.276
		0.0000*	0.0000*	0.0000*				0.00*	0.00*	0.00*		
SIMPAR	EGARCH(1.1)	3.669	0.012	0.648		4.323	TGARCH(1.1)	0.676	11.635	0.009		5818.185
		0.0000*	0.3735	0.0000*				0.00*	0.00*	0.00*		
SIPHAT	EGARCH(1.1)	1.127	0.036	0.606		1.752	EGARCH(1.1)	4.52	−3.544	0.901		3.65
		0.0000*	0.064**	0.0000*				0.00*	0.00*	0.00*		
SITS	EGARCH(1.1)	1.037	0.104	0.703		1.792	TGARCH(1.1)	0.026	0.002	0.967		0.994
		0.0000*	0.0000*	0.0000*				0.00*	0.795	0.00*		
SOMOCER	EGARCH(1.1)	1.176	0.284	0.666		1.984	EGARCH(1.1)	0.421	0.312	0.923		1.5
		0.0000*	0.0000*	0.0000*				0.00*	0.00*	0.00*		
SOTETEL	GJR-GARCH(1.1)	1.04	−0.186	0.22		1.166	TGARCH(1.1)	0.022	0.038	0.901		0.941
		0.0000*	0.0000*	0.0000*				0.291	0.177	0.00*		
SOTRAPIL	EGARCH(1.1)	1.575	0.157	0.763		2.416	TGARCH(1.1)	0.002	0.356	0.652		0.832
		0.0000*	0.0000*	0.0000*				0.923	0.00*	0.00*		
SOTUMAG	PGARCH(1.1)	0.567	−0.084	0.388	1.05	0.912	EGARCH(1.1)	35.659	−34.719	0.492		18.792
		0.0000*	0.0000*	0.0000*	0.0000*			0.00*	0.00*	0.00*		
SOTUVER	EGARCH(1.1)	0.419	0.052	0.995		1.44	PGARCH(1.1)	7.225	0.901	0.56	0.847	8.236
		0.0000*	0.0000*	0.0000*				0.00*	0.00*	0.00*	0.00*	
SPDIT-SICAF	GJR-GARCH(1.1)	1.052	−0.017	0.2		1.243	GJR-GARCH(1.1)	177.337	0.937	0		177.805
		0.0000*	0.2995	0.0000*				0.00*	0.00*	1		
STAR	EGARCH(1.1)	1.06	0.255	0.668		1.855	TGARCH(1.1)	0.04	−0.004	0.938		0.975
		0.0000*	0.0000*	0.0000*				0.00*	0.695	0.00*		
STB	EGARCH(1.1)	1.153	0.286	0.685		1.981	TGARCH(1.1)	0.014	0.007	0.956		0.974
		0.0000*	0.0000*	0.0000*				0.267	0.529	0.00*		
TPR	GJR-GARCH(1.1)	2.763	−0.391	0		2.568	TGARCH(1.1)	0.646	−0.661	0.497		0.812
		0.0000*	0.0000*	0.4839				0.00*	0.00*	0.00*		
TUNINVEST-SICAR	PGARCH(1.1)	0.734	−0.212	0.138	0.544	0.766	GJR-GARCH(1.1)	38.767	0.824	0.01		39.189
		0.0000*	0.0000*	0.0000*	0.0000*			0.00*	0.00*	0.00*		
TUNISAIR	PGARCH(1.1)	0.944	−0.346	0.219	0.924	0.99	TGARCH(1.1)	0.275	−0.319	0.908		1.023
		0.0000*	0.0000*	0.0000*	0.0000*			0.00*	0.00*	0.00*		
TUNISIE LEASING	PGARCH(1.1)	0.872	−0.469	0.227	0.603	0.864	GARCH(1.1)	0.01		0.984		0.995
		0.0000*	0.0000*	0.0000*	0.0000*			0.025		0.00*		
UIB	EGARCH(1.1)	1.193	0.22	0.735		2.038	TGARCH(1.1)	0.054	0.052	0.68		0.76
		0.0000*	0.0000*	0.0000*				0.276	0.33	0.00*		

* Significant at the 1% level.
** Significant at the 5% level.
*** Significant at the 10% level.

types of news had a different impact on the conditional volatility. The specification of the conditional variance according to Nelson (1991) is translated as follows:

$$Ln(h_t^2) = \alpha_0 + \sum_{i=1}^{p} \alpha_i \left| \frac{\varepsilon_{t-i}}{\sigma_{t-i}} \right| + \sum_{j=1}^{q} \beta_j Ln(\sigma_{t-j}^2) + \sum_{k=1}^{r} \gamma_k \frac{\varepsilon_{t-k}}{\sigma_{t-k}} + \varepsilon_t$$

α_i measures the effect of the passed error term. β_j measures the recurrence relation between the conditional variance to that of the previous period. γ_k captures the effect of error sign. The presence of "leverage effect" can be tested by the hypothesis that $\gamma_k < 0$ and the impact is asymmetric if $\gamma_k \neq 0$. If $\gamma_k = 0$, a positive shock had a higher impact on volatility than a negative shock. If $\gamma_k < 0$, a positive shock generates less volatility than a negative shock. If $\gamma_k > 0$, a negative shock generates less volatility than a positive shock. The advantage of using natural logarithm is to ensure the positivity of the conditional variance. That is why it is not necessary to impose restrictions on the parameters of positivity.

- GJR-GARCH (p, q) process of Glosten et al. (1993)

Glosten et al. (1993) have developed a modified GARCH process that is able to capture adequately the asymmetrical effect of disturbances on the conditional variance. GJR-GARCH model is a modification of the original GARCH model by adding a dummy variable. The equation of the variance, according to Glosten, Jagannathan and Runkle (1993), adopted this formulation:

$$h_t^2 + \alpha_0 + \sum_{i=1}^{p} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{q} \beta_j \sigma_{t-j}^2 + \sum_{k=1}^{r} \gamma_k \varepsilon_{t-k}^2 I_{t-k}^- + \varepsilon_t$$

where I_{t-k}^- is a dummy variable, that is:

$$I_{t-k}^- = \begin{cases} 1 & si\varepsilon_{t-i} < 0, & \text{Bad news} \\ 0 & si\varepsilon_{t-i} \geq 0, & \text{Good news} \end{cases}$$

In this model, the impact of bad news and good news on the conditional volatility is completely different. The good news has an effect on α_i while a bad news has an effect on $\alpha_i + \gamma_k$. If $\gamma_k > 0$, bad news increases the conditional volatility and therefore we can confirm the existence of leverage effect. If $\gamma_k \neq 0$, the impact of the new (shock) is asymmetric.

- TGARCH (p, q) process of Zakoian (1994)

TGARCH model (Threshold GARCH) of Zakoian (1994) is similar to the GJR-GARCH specification except that it indicates the asymmetry on the conditional standard deviation and not the conditional variance. This model may have the following wording:

$$h_t = \alpha_0 + \sum_{i=1}^{p} \alpha_i \varepsilon_{t-i} + \sum_{j=1}^{q} \beta_j \sigma_{t-j} + \sum_{k=1}^{r} \gamma_k \varepsilon_{t-k} I_{t-k}^- + \varepsilon_t$$

- PGARCH (p, q,δ) process of Ding et al. (1993)

Ding et al. (1993) proposed another extension of the GARCH model to take into account the effect of asymmetric shock on volatility. In this model, the conditional standard deviation is modeled rather than the conditional variance. The power parameter δ of the conditional standard deviation is estimated rather imposing. In this specification, the parameter γ_k is added in order to capture the asymmetric effect of news on volatility. The Asymmetric PGARCH can be defined as follows:

$$h_t^\delta = \alpha_0 + \sum_{i=1}^{p} \left(\left| \varepsilon_{t-i} \right| - \gamma_i \varepsilon_{t-i} \right)^\delta + \sum_{j=1}^{q} \beta_j \sigma_{t-j}^\delta + \varepsilon_t$$

γ_k represents a coefficient of leverage effect. δ is a power parameter which takes a positive value. As $\delta > 0$, this means that a negative shock has a higher significant impact on conditional volatility than a positive shock. Indeed, Table A.4 summarizes the different appropriate ARCH models for quoted spread series and for depth-at-best-limit series.

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