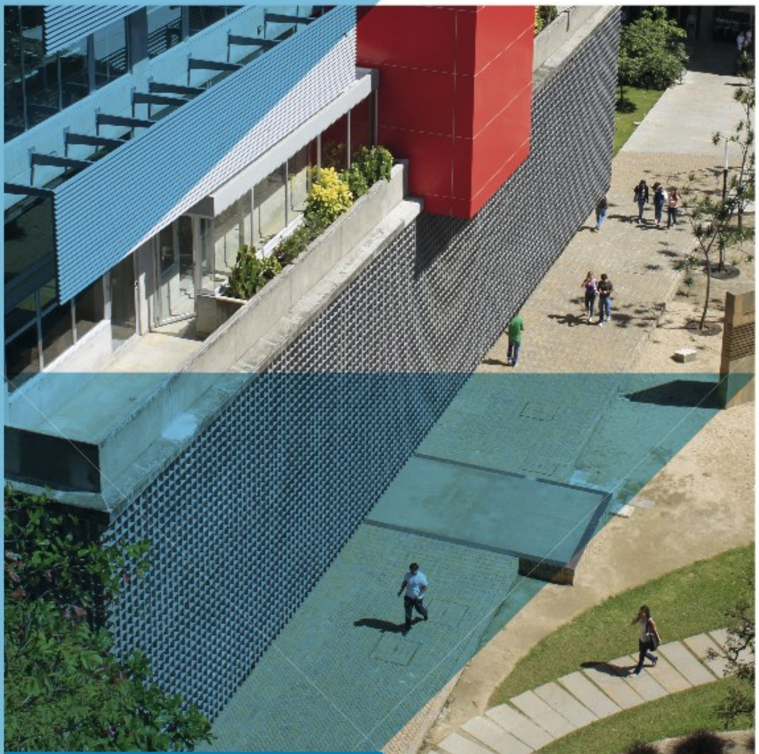

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How does information disclosure affect liquidity? Evidence from an Emerging Market

Abstract

Cross-sectional models positively relate firm information disclosure with stock liquidity, but dynamic models in news releases days show an opposite relation. We address this puzzle by studying the effects of information arrival on liquidity and its determinants. We use trade and quote data from Colombia for 2015 and 2016, along with the complete database of news releases as reported by companies to the regulator. The results of Panel data and PVAR models suggest that news releases increase both informed and uninformed trading. All in all, the temporal negative effect of news releases on liquidity is explained by increasing asymmetric information.

JEL: G10, G15, G19

Keywords: Liquidity, Asymmetric Information, Informed Trading, News releases, Emerging Markets.

1 Introduction

Firms have incentives to improve market quality of their securities via increased revelation. Among other things, this should lead to reductions of cost of capital and liquidity risk on their listed securities (Diamond and Verrecchia, 1991). However, empirical findings suggests that liquidity lowers around announcement times, because of larger adverse selection costs (Krinsky and Jason, 1996; and Koski and Michaely, 2000). Puzzlingly, liquidity is positively related to transparency, measured by news releases across stocks, but, at the same time liquidity drops during news releases days.

According to the models of Holthausen and Verrecchia (1990) and Kim and Verrechia (1997), announcements should increase the activity of informed traders, as they seek to exploit their private information, before and on the announcement. This is further complicated by the endogenous nature of liquidity, which forms simultaneously with other trading variables such as return, volatility and trading activity. Furthermore, these liquidity determinants are also affected by news releases (Grob-klubmann and Hautsch, 2011; Riordan, Storkenmaier, Wagener, and Zhang, 2013). Since the liquidity determinants are affected simultaneously on days of announcements, it is no clear how those variables interact each other to render a lower liquidity. To investigate this, this study looks into how the information arrival process affect both liquidity and information asymmetry and its determinants.

We use the Colombian stock markets as a case study, taking advantage of a first-hand source of information: the database of firm announcements to the ”Superintendencia Financiera”, the Colombian financial regulatory entity (henceforth SF). By law, Colombian public firms are required to report material information as soon as possible and first at all to the SF before to any news company. Usually the information is reported electronically to the SF and soon after, learnt by news companies and traders from the SF database. We choose Colombia due to the availability of high-quality revelation data and for the strict procedures for information revelation for listed stocks have standards of corporate governance and fluent channels of information transmission[1]. In contrast, other studies use companies specific news such as Yahoo! Finance and Raging Bull (Antweiler and Frank, 2004), Wall Street Journal (Tetlock 2010) and Thompson Reuters (Grob-klubmann and Hautsch, 2011; Riordan et al, 2013).

[1] Listed firms in the Colombian stock market must comply with the corporate governance referents indicated in the regulations number 275 from 2001 (República de Colombia and Superintendencia Financiera, 2001).

We start by examining the news effect on liquidity and its determinants, applying panel data models to account for the cross-sectional and dynamic effects. However, market microstructure models (Roll, 1984; Hasbrouck, 1995) recognize that trading characteristics are jointly determined. Consequently, we run panel vector autoregressive (PVAR) models to account for this endogeneity. Several recent papers have been using this approach to capture dynamic interdependencies of endogenous variables in a panel data setting, but to the extent of our knowledge, this is the first in doing so to model liquidity[2].

Accordingly, we contribute to the literature by testing the interaction between liquidity and its determinants, overall and during news releases days. Thus, we are able to confirm the negative temporal relationship between liquidity and news and to find what determinants explain this effect. In this way, we shed light on the process by which information is incorporated to prices in the trading process, particularly in days of public information. Using the case of Colombia is also interesting for being not only an emerging market, but also a pure limit order book market, without designated liquidity makers. Thus, the results of this study serve as an out-of-sample test of some theoretical models and empirical findings in market microstructure, most of the latter coming from US stock markets.

Our main results can be summarized as follows. We find that volatility, number of trades and information asymmetry have distinctive effects on liquidity in days of news, as given by their marginal effect in those days. First, a lower marginal effect of volatility on days of news helps to improve liquidity rather than decrease it. Second, both the total and marginal effects of number of transactions on the liquidity are positive. Thus, trading activity improves liquidity overall, and all the more in days of news releases. Third, both the total and marginal effects of order imbalance on liquidity are negative, which is consistent with the implications of theoretical models on the effect of information asymmetry on liquidity (Kyle, 1985; Glosten and Milgrom, 1985; Easley and O´Hara, 1992). Moreover, after controlling for this marginal effect, we find that liquidity does improve in news release days. In other words, the increasing information

[2] Some of the recent studies that use panel vector autoregressive models (PVARs) are: Love and Zicchino (2006) to investigate the relationship between firm's investment decisions and financial development at corporate level. Hristov, Hülsewig, and Wollmershäuser (2012) to study the macroeconomic effects on loan supply shocks at country level. Grossmann, Love, and Orlov (2014) to estimate the relationship between exchange rate volatility, macroeconomic and financial variables at country level. Galariotis, Makrichoriti, and Spyrou (2016) to research the spillover effects from a financial crises in sovereign CDS spreads. Finally, Mcgregor (2017) to measure macroeconomic responses to global commodity prices shocks.

asymmetry in news days sufficiently explains the drop in liquidity. All in all, since news releases attracts both informed and noise traders the net effect is an increase in both trading activity and volatility, but a reduction in liquidity. In summary, our evidence suggests that while news releases reduce liquidity temporally, for an information asymmetry effect, overall they have a beneficial effect on liquidity.

The most related papers to ours are Grob-klubmann and Hautsch (2011) and Riordan et al. (2013) who study the impact of news on microstructure characteristics using VAR models in London Stock Exchange and Toronto Stock Exchange, respectively. We have three main differences with both studies. First, we use of panel data and PVAR. The panel data model studies the contemporaneous reactions of news, liquidity determinants and interactions, controlling by heterogeneities between stocks, whereas the PVAR goes further by modelling the dynamic of the variables and controlling for endogeneity. Second, we study the interactions between liquidity determinants and news releases, allowing us to observe the incremental effects on these variables in days of information arrival. Third, we study data from an emerging market, a particularly good object of study, because their lower liquidity and efficiency, and lower revelation standards, compared to developed markets.

The rest of this paper is organized as follows: Section 2 provides the background from the related literature. Section 3 describes the data. Section 4 explains the methodology. Section 5 presents descriptive statistics. Section 6 presents the results and discussions of empirical analysis and Section 7 concludes.

2 Background

2.1 News and Liquidity

Classical models such as Kyle (1985), Glosten and Milgrom (1985) and Easley and O'Hara (1992) postulate that informed trading increases adverse selection cost for liquidity providers. They infer the probability of informed trading from imbalances in the incoming order flow. Therefore, market makers reduce liquidity by setting larger bid-ask spreads and price impact to mitigate their losses. Diamond and Verrecchia (1991) broadens this theory by including the effect of information disclosure. They pose that information release, by mitigating adverse selection costs, attracts a large demand of investors (e.g. institutional traders) and reduces firm's cost of capital. Cross section studies provide empirical support for this theoretical negative relationship between information asymmetry and the firm's information disclosure. Brown and Hillegeist (2007), and Sankaraguruswamy, Shen, and Yamada (2013) find that the firms with higher quality disclosure present lower levels of information asymmetry over a long time frame.

However, the existing literature on dynamic models is not entirely consistent with the previous results. Krinsky and Jason (1996) and Koski and Michaely (2000) report higher adverse selection cost components of the bid-ask spread around earnings and dividend announcements, respectively. As a possible explanation they point to the apparently slow reaction of uninformed traders to the news events. Instead, informed-based traders should react more rapidly to exploit their edge (Kim and Verrecchia, 1994). Accordingly, Riordan et al. (2013) show that negative (positive) news releases reduce (improve) liquidity at the time of publication, by augmenting adverse selection cost.

From the previous discussion, we expect that the presence of news would generate information asymmetry and reduce liquidity. In this regard, there are some other liquidity characteristics that are also affected by disseminating firms´ information. Kalev, Liu, Pham, and Jarnecic (2004) present empirical evidence that volatility is proportional to the rate of information arrival. Hence, we expect an increase in volatility when information arrives. Kim and Verrecchia (1994) argue that trading volume becomes higher at the time of earnings announcements. They suggest that the increase in trading activity comes, at least in part, from informed trading.

2.2 Liquidity determinants

The literature on market microstructure discusses relations between trading variables determinants of liquidity: volatility, trading activity, order imbalance and returns. There is an extensive literature showing a positive relation between trading activity (traded volume or number of trades) and volatility. This includes Karpoff (1987), Jones, Kaul, and Lipson (1994), Downing and Zhang (2004), Wang and Wu (2015) between others. From the perspective of information, news arrival leads to disagreements among traders leading to trading prices to move more erratically. In turn, Chordia, Roll, and Subrahmanyam (2002) report, at market level, a negative relationship between the absolute value of order imbalance and trading activity. They also argue that order imbalance is related to prices declines because of the temporary inventory imbalances found when prices are fast dropping. There is also evidence that positive stock returns reduce inventory costs for liquidity providers, resulting in lower spreads (Chordia, Sarkar, and Subrahmanyam, 2005).

The strong positive relationship between volatility and liquidity has been explained twofold. First, inventory costs models (Ho and Stoll, 1981) imply that higher volatility levels represent an increased risk of an adverse price change for the market makers. Second, Roll (1984) model makes explicit the strong link between the bid ask bounce and intraday volatility. Empirical studies such as Fujimoto and Watanabe (2004) and Chordia et al. (2005) confirm this negative relation between volatility and liquidity at market level. Other empirical studies have reported a positive relationship between trading activity and liquidity (Stoll, 2000; Lesmond 2005; Fujimoto and Watanabe, 2004). A more frequent trading mitigates for the liquidity provider the risk of not finding counterparties to balance their positions (Ho and Stoll, 1981).

3 Data

We use a trades and quotes database collected from Bloomberg, from January 2, 2015 to November 22, 2016 [3]. This contains intraday data for 42 companies listed in the Colombian Stock Market[4]. From this database we exclude the trades occurred in volatility call auctions and closed call auctions, to focus only in the continuous market[5].

We collect data on the news releases for the listed companies from the web site of the financial regulatory entity "Superintendencia Financiera" (SF), which publish in real time the firm's announcements. The issuers of securities are required to communicate the relevant information6. The information will be disclosed by the issuer immediately the situation occurs

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[3] Bloomberg only stores 6 months of intraday data, so this data set had to be manually downloaded in four times along the two years.

[4] We exclude 17 companies in total from the sample. We omitted stocks with low levels of trading activity (less than three transactions per day in average) and the dual claim stocks and leave only one type of security for a given firm.

[5] Volatility call auctions last between 2-3 minutes and are triggered by large variations in trading prices. Closing call auctions are scheduled at the last minute of the trading day. We identify those call auctions using a proprietary database from the Colombian Stock Exchange "Bolsa de Valores de Colombia".

[6] República de Colombia and Superintendencia de Valores (2015)

or immediately the issuer becomes aware of the fact when the information originates in a third party. Once the information is reviewed and published in the SF site, it becomes available for the news companies and the general public. Thus, the time stamp of publication, as appears in the news releases database, tell us the hour and the day when the information was known by the market. Table 1 shows the information categories contained in the data. Press releases and the organizational structure category represents up to the 50% of the news data. Organizational structure corresponds to the corporation changes or events related to its economic activity. The remainder corresponds to stock issues and repurchases notices, accounting adjustments to the financial statements, credit score reporting changes and capex investment.

4 Methodology

This sections explain the variables definition and the econometric strategy to estimate the interacting effects between news releases and liquidity determinants, based on both panel data and panel VAR models.

4.1 Liquidity Measure

We use two measures to describe the daily effective illiquidity. The first measure is the effective spread as in Goyenko, Holden, and Trzcinka (2009) and Fong, Holden and Trzcinka (2017), identified by both studies as a liquidity benchmarks based on intraday data.

$$Eff\_Spread_\tau = 2\ |log(P_\tau) - log(M_\tau)| \qquad (1)$$

Where P_τ is the trade price at the transaction "τ", and M_τ is the midpoint between the bid-ask before the trade is completed. The daily effective spread Eff_Spread_t is the average of this measure computed over all trades during the day.

Similarly, we define our second illiquidity measure as the quoted bid-ask spread. This measure is also defined for each trade, as follows:

$$Bid\text{-}Ask\_Spread_\tau = log(Ask_\tau - Bid_\tau)/ M_\tau \qquad (2)$$

Where, $Bid\text{-}Ask\_Spread_\tau$ is the quoted bid-ask spread before the transaction "τ". Ask_τ is the prevailing best ask price and Bid_τ the prevailing best bid price before the transaction, and M_τ is the midpoint average between those two. The daily quoted bid-ask spread ($Bid\text{-}Ask\_Spread_t$) is the average of the bid-ask spreads computed over all trades during the day.

4.2 Liquidity Determinants

We calculate the following daily liquidity determinants from the intraday database for the continuous market: daily return, daily trading value, intraday volatility, number of trades, closing price, and order imbalance[7]. Previous studies have used these trading characteristics as control variables to model liquidity in panel data or VAR settings[8].

The daily return is computed with close-to-close prices (close prices of the continuous market, not of the closing call auction). Intraday volatility is estimated as the daily range, the log difference between the highest $HighPrice_t$ and lowest price $LowPrice_t$ of a day (Alizadeh, Brandt, and Diebold, 2001).

$$\sigma_t = log(HighPrice_t) - log(LowPrice_t) \qquad (3)$$

These authors report that the daily range is highly efficient estimator of volatility and avoid the limitations of stochastic volatility models, and generalized method of moments and likelihood-based estimation through numerical integration. Recent papers such as Wang (2007), Chiang and Wang (2011), Wang and Wu (2015) and Yepes and Agudelo (2016) have used this volatility measure

Following Chordia et al. (2002), we define the order imbalance measure as absolute value of the standardized difference between the buys and sells, as follows: .

$$|OIB_t| = |\underline{Buys_t - Sells_t}| \; / \; NT_t \qquad (4)$$

Where $|OIB_t|$ is the absolute value of order imbalance for the day t. $Buys_t$ are the number of buyer-initiated on the day t, $Sells_t$ are the number of seller-initiated on the day t and NT_t is the total number of trades on the day t. We use the Lee and Ready (1991) algorithm to classify the buys and sells.

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[7] Trading value is preferred to Volume (number of traded shares), because of the wide of price ranges of stock in the Colombian Stock market, going from 10 to 60.000 Colombian pesos (COP). For example, this would make inappropriate to compare a trade of 10 million shares in a stock at 20 COP per share, that the same number of shares in a stock with a price around 50.000 COP

[8] See for example Grullon, Kanatas, and Weston (2004), Lesmond (2005), Agudelo, Giraldo, and Villarraga (2015), Grob- klubmann and Hautsch (2011), Riordan et al. (2013) between others.

4.3 News effect on control variables and Liquidity: Panel Data Model

As a first approximation in the relation between liquidity and news, we regress a fixed effects panel data models commonly used in the literature to model the bid-ask spread[9]. We control for the liquidity determinants, and include a news variable $News_{it}$ as a dummy with the value of one for those stock-days with news releases and zero, otherwise. The equation model is given as follows:

$$\begin{aligned} Illiquidity_{it} &= CtrlVbles_{it} + \delta_1 News_t + \delta_2 CtrlVble_j * News_{it} + \varepsilon_{it} \\ CtrlVbles_{it} &= \beta_1 r_{it} + \beta_2 log(NT_{it}) + \beta_3 log(vol_{it}) + \beta_4 \sigma_{it} + \beta_5 log(price_{it}) + \beta_6 \, |OIB_{it}| . \end{aligned} \quad (5)$$

Where $Illiquidity_{it}$ are alternatively Eff_Spread_t and $Bid\text{-}Ask\_Spread_t$, r_{it} is the daily return, $log(NT_{it})$ the log of the number of trades, $log(vol_{it})$ the logarithm of daily trading value, σ_{it} the intraday volatility defined in (3), $log(price_{it})$ the log of the closing price, and $|OIB_{it}|$ the order imbalance measure. We include both trading value along with the number of trades as trading activity variables, to account for the average size of the orders. $CtrlVble_j * News_{it}$ represents interactions between the news variable and each one of the liquidity determinants.

4.4 News effect on control variables and Liquidity: Panel VAR

We use the panel vector autorregression (PVAR) model with fixed effects to model the interactions between trading variables in days of news[10]. The main advantage of PVAR model over the traditional panel data regression is that treat all variables as endogenous. We deem this as particularly relevant for this study since market liquidity and other trading variables are jointly determined in the trading process (Kyle, 1985; Glosten and Milgrom, 1985; Easley and O'Hara, 1992). By including fixed effects, this model also allows to account for cross-sectional unobserved heterogeneities between stocks. Finally, the PVAR model is able to capture

[9] Grullon et al. (2004), Lesmond (2005), Cesari, Espenlaub, and Khurshed (2011), Agudelo et al. (2015)

[10] We are indebted to Love and Zicchino (2006) for developing the PVAR model procedure as a package of the statistic software STATA.

dynamic interdependencies among liquidity and its determinants by including their lags. It also controls for common time effects, such as systematic liquidity such as systemic liquidity (Chordia, Roll, and Subrahmanyam, 2000; Huberman and Halka, 2001). The one-lag panel VAR model in reduced form can be written as follows:

$$Y_{it} = AY_{it-1} + f_i + d_t + e_{it}$$
$$Y_{it} = [\ News_{it},\ \ |OIB_{it}|,\ Return_{it},\ log(NT_{it}),\ log(Trad\_value_{it}),\ \sigma_{it}\ ,\ log(Bid\text{-}Ask\_Spread_{it})\ ]^T \tag{6}$$

Where Y_{it} is the vector of endogenous variables for the stock i, A is a matrix of autoregressive coefficients for lag one, f_i is a vector of fixed effects which captures the unobservable firm-specific levels, and d_t is a dummy variable to capture common time effects[11].

We select one lag as the optimal autorregresive order for our system using the information criteria of Akaike, Schwartz and Hanan and Quinn. To order the variables from the least to the most endogenous, we start from theoretical considerations. The news variable has to be the most exogenous one, representing days when the firm releases information. Next, we place the order imbalance as proxy of asymmetric information assuming that appears once information arrives. Later, we place stock returns assuming market efficiency, this is, prices are adjusted immediately to the information direction. Finally, we have trading activity and volatility as interacting variables and assume liquidity to be the most endogenous. We test this proposed ordering using the method of variance decomposition of Cholesky. Table 2 summarizes the results, presenting the percentage of the own-explained variation for each variable, (henceforth, ”own variance”) averaged across stocks, for the 10^{th} period ahead. From table 2, we identify the most exogenous variable with the higher value in their ”own variance”. The results shows that 75% of the times *News* variable was more exogenous than its successor. Thus we keep this variable in the first place. $|OIB|$ and stock return were equally likely to be in

[11] Since the explanatory variables are lags of the dependent ones, time-invariant factors are correlated with regressors. Thus, the procedure of first-difference to remove panel-specific fixed effects would generate biased coefficients. Instead, we implement forward mean-differencing, also referred as the ”Helmert procedure” proposed by Arellano and Bover (1995). This method maintains orthogonality between fixed effects and lagged regressors. Equation (6) represents the reduced form of the VAR approach which contains only the lagged effects. Thus, the contemporaneous structural shocks of each variable are contained into the error term e_{it}. To isolate the orthogonal shocks to any one of the variables in the model, we use the Cholesky decomposition of the variance-covariance matrix of the residuals e_{it} (see Hamilton, 1994). Then, we replace time dummies d_t by subtracting the cross-sectional mean from each variable in the system , following Hristov et al. (2012), Grossmann et al. (2014) and Berdiev and Saunoris (2016). This procedure is equivalent to maintain the dummies in the model.

second place, but we assume $|OIB|$ to be the most exogenous. Then, number of trades is always below than stock returns. The trading value presents low ”own variance” values, but we keep it after $log(NT)$ for being another trading activity variable. Besides, 96% of the times volatility presents lower ”own variance” percentages that the number of trades and 63% of the times is upper than illiquidity. Finally, the last row of the table present the averages of the ”own variances” and support the ordering of endogeneity of the variables mentioned above[12].

Finally, in alternative PVAR models we interact out news dummy variable with each liquidity determinant. Our interactions are located in the vector Y after the two variables interacted to maintain the same ordering of the Chokesky procedure. Like in the Panel data model, we run a different regression for each interaction term in order to avoid overidentification.

5 Descriptive Statistics

We presents descriptive statistics to compare the relationship of liquidity to news releases in both cross-sectional and time series approaches. Figure 1 [12] shows the relationship between the total of news releases and average liquidity for the stocks in the sample, and Table 3 lists the data for each stock. This graph suggests that companies with more news releases tend to have a lower daily average of bid-ask spread. This is consistent with static studies (Brown and Hillegeist, 2007; Sankaraguruswamy et.al. 2013) reporting that firms with more information disclosure attain higher liquidity levels, even after controlling by information asymmetry proxies, trading activity and other market microstructure variables. Table 4 confirm the negative correlation between the total news with both illiquidity measures.

Table 4 also shows the cross-correlations between pairs of characteristics. First, we discuss the bivariate relationship between illiquidity measures and their determinants (Columns (1) and (2)). Liquidity appears positively and significantly related to trading activity (both traded value and number of trades) and negative related to the absolute value of order imbalance. This is consistent to the market microstructure theories suggesting that informed trading, proxied by imbalances in the order flow, decreases liquidity because the resulting adverse selection cost on liquidity providers (Glosten and Milgrom, 1985; Easley and O'Hara, 1992). Similarly to the previous analysis, higher levels on volatility also increase liquidity provider costs which results in higher bid-ask spreads (Ho and Stoll, 1981). Finally, empirical studies such as Stoll (2000)

[12] As indicated below, we confirm our results with some reasonable alternative order of the variables.

and Lesmond (2005) explain with inventory costs the positive relationship between trading activity and liquidity. From the microstructure perspective, trading activity reflects not only the information arrival but also when traders have different opinions and interpretation of that information, and the presence of noise trading. Anderson (1996) supports this theory by revealing that a substantial part of the daily volume is unrelated to the information arrival. Thus, since trading activity is largely noisy, it would be associated to a high volatility but not necessarily to the information asymmetry.

Next, we compare the behavior of variables in new releases days and on the previous day from the same stock. Table 5 suggests that illiquidity and volatility increase from days of no-news to a days with presence of news and those differences are statistically significant. There are also non-significant increases in the averages of the two trading activity variable and the absolute value of order imbalance, proxy of informed trading.

We test for the robustness of the results when permuting the order in the PVAR of the variables return, number of trades, trading value and volatility. This is required since these variables are jointly determined in the trading process. Besides, the results of the Cholesky Variance decomposition (Table 2) do not indicate the same exogeneity order among these variables for each stock. The results, not presented here, are available upon request from the authors.

In summary, the preliminary evidence suggest that firms which present the more frequent information disclosing have higher levels of liquidity. This is in accordance with theoretical approaches and cross-sectional studies that indicate that these companies have lower information asymmetry and liquidity risks and therefore lower cost of capital and higher liquidity[13]. However, the information at the time of disclosure appears to have an immediate adverse effect on liquidity, agreeing with previous time series studies[14].

6 Results

This section presents and discusses the results of two alternative approaches to model the relationship between liquidity determinants and the effect of news.

[13] Diamond and Verrecchia (1991), Brown and Hillegeist (2007) and Sankaraguruswamy et al. (2013).

[14] Krinsky and Jason (1996), Koski and Michaely (2000), Riordan et al. (2013).

We start with the results of two alternative panel data regression in each of the two liquidity proxies in Table 6. Panel A reports the results of fixed effect models, whereas Panel B those of a model with panel-corrected errors to avoid cross-sectional dependence. The results of panel data regressions in table 6 support the findings of the descriptive statistics discussed above. In general, we confirm that information asymmetry (proxied by $|OIB|$) and volatility are positively related to the illiquidity measures. Also, we find that the higher the number of trades, the more liquid the stocks, but the trading value, contrary to the expected, is negatively related to the stock liquidity. This appears to be simply the consequence of controlling for number of trades that render the trading value to be only explaining the daily average size of trades. Trade size has been related to informed trading (Easley and O'Hara (1987) and the price impact of large orders (Madhavan, 2000). Similar relationships have been reported on the US market by Downing and Zhang (2004), Ozsoylev and Takayama (2010) Wang and Wu (2015) between others.

6.1 Liquidity Determinants and News releases

In table 7 we report results from the orthogonalized impulse response functions (OIRF) up to 3 periods ahead. The OIRF's are estimated from the PVAR model (6) as the incremental effect on each variable in the row over time following a orthogonalized shock to the variable in the column.

The column (1) shows the impact of our variable of interest, news releases, on liquidity and its determinants. First, this confirms the negative effect of news releases on liquidity. This effect is statistically significant but short lived, not going beyond the release day. This partially agrees with the findings of Riordian et al (2013) that finds the same effect for negative news but not for neutral or positive. In the last row of Table 7, the effects of shocks of the trading variables on liquidity also appear significant and with the sign reported in Table 6. The effect of Order Imbalance, proxy of informed trading, and number of trades appear statistically significant even after three days.

Besides, news releases have a positive effect on volatility and that this response is still significant after three days. This goes along with the findings of Kalev et al. (2004) who report a time dependence of volatility to the rate of the public information arrival.The news releases also impact positively on trading activity measured both by trading value and number of trades. This is consistent to Chordia, Roll, and Subrahmanyam (2001) argument that announcements induce more trading activity by attracting both informed and non-informed traders. The news releases are also positively related to the asymmetric information proxy

($|OIB|$). This supports the notion that news are informative to the market and that at least part of the increasing trading reflects the activity of informed traders (Kim and Verrecchia, 1994; Krinsky and Jason, 1996; Koski and Michaely 2000).

To complement the previous results, we examine in columns (2) to (6) the impulse-response among the trading variables. First, there is a clear persistence on each variable to its own shocks, consistent with well-known autoregressive behaviors in financial series. For example, Chordia et al. (2002) show that order imbalances are highly persistent and volatility presents clusters among time-series (Kavajecz and Odders-White, 2001) which is often accounted by autoregressive conditional heteroskedasticity regression models (GARCH).

The column (3) of table 7 shows that a positive shock in stock returns attracts trading activity, reduces volatility and increase liquidity. This last result is consistent with empirical findings of positive returns associated to lower bid-ask spreads (Chordia et al. , 2001; Stoll 2000). In turn, the negative impact of trading activity on spreads reported in column (4) of table 7 confirms the cross sectional findings above and those of Stoll (2000) and Lesmond (2005). In turn the positive effect of trading value on spread is short-lived, and tends to reverse in the few following days (column (5)).

In column (6) we present evidence of a negative relationship between volatility and liquidity, i.e. volatility shocks lead to higher bid-ask spreads. This is expected from the Ho and Stoll (1981) model that identify volatility of the security as a reason for a risk-averse liquidity provider to increase bid-ask spreads. This relationship is also reported at market-level in the empirical findings of Fujimoto and Watanabe (2004) and Chordia et al. (2005). Finally we find a two-way positive relationship between trading activity and volatility, significant even after three days. This can be explained from the perspective of new information: trading activity increases by attracting investors in disagree about the meaning of the information (Karpoff (1987) which in turns leads to price instability. Besides, the volatility of stock prices also attracts trading activity especially from day traders (Kyröläinen 2008). Column (6) also show a persistence of the effect of volatility on trading activity. This is consistent to Downing and Zhang (2004) who find a positive relation between trading activity and volatility. They argue that this relationship depends on institutional investors trading large volumes among them, to reduce transaction costs.

6.2 Interactions between Liquidity Determinants and News releases

To investigate the mechanisms of the effect of news releases on liquidity, we examine how interactions between the trading variables and news releases affect liquidity. Table 8 shows the results for the panel data regressions (5). Including in the panel data the interactions of the liquidity determinants with news, one at the time, we are able to measures the marginal effects on liquidity, in days of news releases as presented in columns (1) to (6). Further, although the coefficient of news in the base case regression (column (1)) has low statistical significance, it becomes more significant by including some of the mentioned interactions.

In the case of volatility, the negative coefficient of its interaction with the news variables suggest that news releases reduce the positive effect of volatility on bid-ask spreads. Moreover the isolated news effect on liquidity becomes more negative and significant. We interpret this result as informed trading becoming an increasingly factor over volatility in determining liquidity in days of news, as explained below. Regarding to the number of transactions, we find that its marginal effect on bid-ask spreads on news days is negative, like the unconditional effect. In other words, the positive effect of trading activity (measured as number of transactions) on liquidity is magnified by the presence of the information arrival. This is consistent with the empirical findings of Grob-klubmann and Hautsch (2011) and Riordan et al. (2013). Both studies examine high- frequency data and show similar responses to news arrivals in microstructural variables such as bid-ask spreads, trading volumes, volatility and returns.

The last column of table 8 presents the interaction between order imbalance and news releases. This result indicates that the order imbalance in presence of news, decreases liquidity. This is expected, since the informed trading proxy, $|OIB|$, should be more correlated with information asymmetry in days of news releases. Also, interestingly, the negative coefficient in the news variable in column 8 suggest that $|OIB|$ completely reverses the isolate effect of news, subsuming the negative effect of the news on liquidity. This is confirming evidence in the validity of the order imbalance as proxy of informed trading.

Since liquidity determinants are caused simultaneously and the panel data approach do not account for this, we use the PVAR model (6) with the inclusion of the same interactive variables, once at the time. Table 9 presents the estimates of this model for the interactions effects on liquidity, validating the previous results. Order imbalances in news days reduces liquidity up to two days after. This is further evidence that asymmetric information presented on days with news reduces more liquidity than in no news days. In turn, the incremental negative effect of both trading activity and volatility on bid-ask spreads on days in news days is not only confirmed but appear significant up to three days after. In addition, panel VAR allows to measure the spillover effect over time after a contemporaneous shock. Overall the OIRF results show that the temporal effect of news on liquidity through liquidity determinants lasts between two and three days.

7 Conclusions

In this paper, we analyze how news releases affect liquidity and its determinants. To this end, we make use of two datasets, the trades and quotes collected from Bloomberg and the firm's news announcements from the Colombian financial regulatory entity "Superintendencia Financiera". In the contrast to the existing literature, we examine both the net effect of market variables and its marginal effects on liquidity conditional to the presence of news releases.

Our main results provide evidence of the existence of interacting effects between the main liquidity determinants and news releases. In general, we find that news announcements impact directly the trading variables that determine liquidity but also modify their effect on liquidity. We have found that the marginal effect of volatility in presence of news releases on illiquidity is negative which is opposite to the total effect. The marginal effect of the variable of the number of transactions on liquidity is negative and it is aligned to the total effect. More importantly, informed trading, as proxied by the absolute value of order imbalance, has the same increases its negative effect on liquidity in news days. Furthermore, it´s the only of the trading variable that captures the negative total effect of news on liquidity. These results are consistent with news releasing important for liquidity formation in this emerging Market, via informed trading, and not simply via increasing volatility or trading activity.

We identify implications of this research for both traders and regulators. The traders might acknowledge the temporally negative impact of new releases on liquidity, and consider the higher cost of trading on days of news. On the other hand, exchange regulators could take into account the importance of promoting liquidity in days of news releases.

For future research we leave to study the differential effects of classes of news on the liquidity and trading variables, including macro and firm-specific and positive, negative or neutral. Besides, following a line of studies in Emerging Markets, it´s interesting the differential behavior of types of investors during new releases days. Specifically, what types of investor are trading with information and what types providing liquidity.

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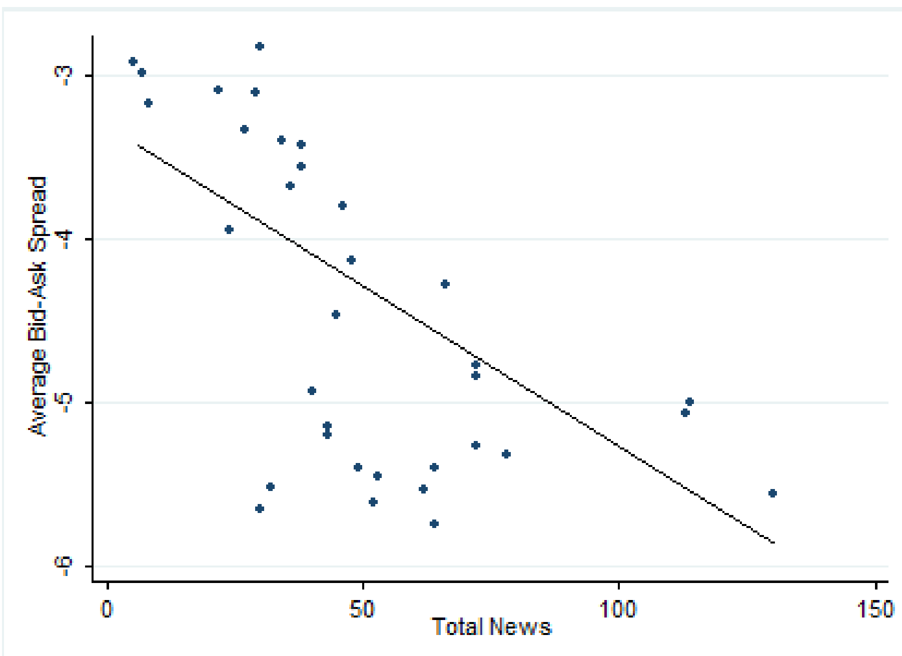
Table 1: Classification of News

Concept	Number of News	Participation
Stock Issues and repurchases	149	4.8%
Accounting adjustments	695	22.2%
Meeting of Shareholders	196	6.3%
Organizational structure	878	28.1%
Press releases	869	27.8%
Credit Score	249	8.0%
Investment decisions	91	2.9%

Note: This table reports the news releases categories contained in our data in the news releases database of Superintendencia Financiera de Colombia, between January of 2015 and November of 2016).

Figure 1: Liquidity and News releases across firms



The figure shows a scatter plot between the averages of the *Bid-Ask_Spread* with respect to total number of news published over the sample time (Between January of 2015 and November of 2016). Each point represents one company, and there is a total of 34 companies with news reported.

Table 2: Cholesky Variance Decomposition

	"Own variance" 10 periods ahead						
	News	$\|OIB\|$	*Return*	$log(NT)$	$log(Trad\_value)$	σ	$log(Bid\text{-}Ask\_Spread)$
GRUPOSUR	98.3	97.4	95.4	91.3	47.4	77.8	57.9
NUTRESA	98.4	97.8	95.9	93.9	28.8	87.9	53.9
CORFICOL	94.3	96.9	98.3	92.4	42.7	87.2	59.1
EXITO	96.7	97.5	95.7	97.1	19.3	64.8	53.3
ECOPETL	97.3	96.1	95.9	90.5	16.4	76.4	59.0
PFAVH	97.9	94.8	97.1	88.8	32.2	53.1	73.9
CNEC	97.8	98.5	96.1	88.0	19.2	65.5	68.3
GRUPOARG	94.8	98.1	96.0	95.6	35.1	84.5	60.9
BCOLO	98.7	97.9	98.0	88.7	30.8	74.9	56.3
ISA	97.8	95.5	97.5	92.6	31.6	79.1	56.0
ISAGEN	97.6	88.5	92.8	74.4	41.2	60.3	57.8
CEMARGOS	94.1	95.3	97.7	86.3	36.4	75.1	58.9
CLH	98.1	95.2	94.7	91.7	35.5	73.8	71.8
EEB	97.9	96.1	95.4	88.9	68.9	72.6	71.4
PREC	93.1	89.2	95.1	84.9	7.3	62.8	56.7
CELSIA	98.1	95.1	96.7	85.7	23.3	74.7	60.7
ETB	96.7	95.5	96.9	80.1	27.4	53.2	66.5
BVC	97.8	97.3	95.6	74.6	31.4	50.2	86.7
AVAL	98.1	95.8	96.8	73.7	44.3	77.1	72.3
CONCONC	95.7	91.5	95.4	74.1	30.9	59.1	81.1
MINEROS	94.8	92.9	90.3	70.2	34.3	68.5	76.8
FABRI	92.1	93.3	88.4	63.5	23.0	53.3	81.2
TERPEL	93.7	93.6	92.7	70.0	48.5	66.8	84.5
ODINSA	88.9	85.7	73.5	68.2	44.4	36.3	62.9
Average	96.2	94.8	94.5	83.6	33.3	68.1	66.2

Note: This table reports the long-run variance decomposition of the variables in the first row for each stock. Specifically, these results represent the percent of variation in the variables that are explained by their own shocks for the 10th period ahead. $News_{it}$ is the dummy for days with presence of news releases. The absolute value of the order imbalance ($|OIB|$) is measured as the standardized difference by number of transactions between buys and sells. *Return* is computed with the daily close to close prices. $log(NT)$ is the log of the number of trades. $log(Trad\_value)$ is the average of the daily traded in local currency. σ is the intraday volatility measured for each day(t) as $\sigma_t = log(HighPrice_t) - log(LowPrice_t)$. The liquidity measure is *Bid-Ask_Spread* as defined in (2). ***, **, and * denote significance at the 0.01, 0.05, and 0.10 levels, respectively.

Table 3: Descriptive Statistics: Cross-section Analysis

Nemo	*log*(*Bid-Ask_Spread*)		*log*(*Eff_Spread*)		Total News
	Mean	Std Dev	Mean	Std Dev	
ECOPETL	-5.557	0.194	-5.162	0.294	130
PREC	-4.999	0.699	-4.943	0.610	114
EEB	-5.063	0.522	-4.866	0.750	113
ISA	-5.322	0.506	-5.290	0.476	78
BOGOTA	-4.778	0.800	-4.898	0.806	72
ISAGEN	-5.272	0.901	-5.134	0.823	72
ETB	-4.846	0.605	-4.882	0.658	72
AVAL	-4.278	0.753	-4.223	0.810	66
GRUPOSUR	-5.749	0.497	-5.794	0.496	64
BCOLO	-5.392	0.663	-5.440	0.675	64
EXITO	-5.527	0.501	-5.431	0.425	62
CNEC	-5.453	0.494	-5.367	0.499	53
CORFICOL	-5.614	0.609	-5.846	0.709	52
GRUPOARG	-5.405	0.488	-5.395	0.453	49
CONCONC	-4.133	0.849	-4.133	0.847	48
ELCONDOR	-3.798	1.153	-3.813	1.205	46
BVC	-4.474	0.439	-5.370	1.969	45
CLH	-5.151	0.496	-5.141	0.473	43
CEMARGOS	-5.202	0.456	-5.195	0.420	43
CELSIA	-4.927	0.666	-4.978	0.646	40
ENKA	-3.436	0.805	-4.257	2.592	38
PFCARPAK	-3.570	0.944	-3.672	1.011	38
FABRI	-3.682	0.708	-4.202	1.973	36
TERPEL	-3.407	1.240	-3.561	1.218	34
PFAVH	-5.524	0.437	-5.267	0.492	32
NUTRESA	-5.650	0.514	-5.636	0.508	30
ODINSA	-2.835	1.238	-3.120	1.270	30
OCCID	-3.111	1.387	-3.352	1.421	29
VALOREM	-3.341	1.385	-3.476	1.290	27
MINEROS	-3.947	0.905	-4.036	0.918	24
PROMIG	-3.094	1.594	-3.323	1.621	22
COLTEJ	-3.173	0.927	-3.197	0.940	8
GRUPOBOL	-2.996	1.543	-3.239	1.558	7
CARTON	-2.924	1.153	-3.197	1.339	5

This table reports summary statistics of the liquidity variables and total news releases for each trading stock. This information is organized in descending order according to the number of news releases. The liquidity measures are *Bid-Ask_Spread* and *Eff_Spread*, defined in (1) and (2), respectively.

Table 4: Pooled Cross Sectional Correlation

Variable	*log(Bid-Ask_spread)* (1)	*ln(spread vol)* (2)	*ln(Eff_Spread)* (3)	*log(Volume)* (4)	σ (5)	$\lvert OIB \rvert$ (6)	*OIB* (7)	*Return* (8)	*ln(NT)* (9)	*News* (10)
log(Bid-Ask_Spread)	1									
log(Spread_vol)	0.662***	1								
log(Eff_Spread)	0.787***	0.437***	1							
log(Trad_value)	-0.228***	-0.178***	-0.224***	1						
σ	-0.068***	-0.044***	-0.019*	0.251***	1					
$\lvert OIB \rvert$	0.453***	0.321***	0.338***	-0.258***	-0.293***	1				
OIB	0.032**	0.011	0.0331***	0.012	0.014	-0.035***	1			
Return	-0.038***	-0.026**	-0.036***	0.031**	-0.044***	-0.028**	0.075***	1		
log(NT)	-0.662***	-0.458***	-0.470***	0.504***	0.425***	-0.561***	0.043***	0.039***	1	
News	0.052***	0.023*	0.058***	0.042***	0.073***	0.025**	0.008	0.001	0.003	1

This table reports the correlation between the averages of trading variables across the 34 stocks. The liquidity measures are: *Bid-Ask_Spread*) defined in (2), *log*(*spread vol*) which is the log of daily bid-ask spread averaged by volume and the *Eff_Spread* defined in (1). Other variables are: *log*(*Trad_value*) is the average of the daily traded value in local currency. σ is measured for each day (t) as $\sigma_t = log(HighPrice_t) - log(LowPrice_t)$. We present both the signed order imbalance (*OIB*) and the absolute value of the order imbalance ($\lvert OIB \rvert$) measured as the standardized difference by number of transactions between buys and sells. *Return* is computed with the daily close to close prices. *log*(*NT*) is the log of the number of transactions. *News* is the dummy variable for days with presence of news releases. ***, **, and * denote significance at the 0.01, 0.05, and 0.10 levels, respectively.

Table 5: Descriptive Stats: Dynamic Analysis

	(A): Day-1 to news		(B): Day of news		(B) – (A)
	Mean	Std. Dev	Mean	Std. Dev	
$log(Bid\text{-}Ask\_Spread)$	-5.007	0.026	-4.961	0.026	0.046*
$log(Trad\_value)$	12.105	0.059	12.164	0.059	0.059
σ	0.020	0.001	0.022	0.001	0.002**
$log(NT)$	2.966	0.042	3.011	0.042	0.045
$\mid OIB \mid$	0.609	0.007	0.613	0.007	0.004
Return	0.000	0.001	-0.001	0.001	0.000
No. of observations	1371		1414		

Note: (A) represents the day previous to news-day, (B) represents news-day. If we have a number of continuous days with news, we use as many days for (A) as there are days of news in a row. For example, if there are 2 continuous days with news, we compare 2 days before the news arrival with the two news-days. Last column present the difference between (A) and (B). t-test is used to compare the statistical significance of these results. *Bid-Ask_Spread* is defined in (2). $log(Trad\_value)$ is the average of the daily value traded in local currency. σ is the intraday volatility measured for each day (t) as $\sigma_t = log(HighPrice_t) - log(LowPrice_t)$. $log(NT)$ is the log of the number of transactions. The absolute value of the order imbalance ($\mid OIB \mid$) is measured as the standardized difference by number of transactions between buys and sells. *Return* is computed with the daily close to close prices. ***, **, and * denote significance at the 0.01, 0.05, and 0.10 levels, respectively.

Table 6: Regressions for liquidity

Model:	(A)		(B)	
Dependent Variable:	*log*(*Bid-Ask_Spread*)	*log*(*Eff_Spread*)	*log*(*Bid-Ask_Spread*)	*log*(*Eff_Spread*)
$Return_{it}$	0.183	-0.073	0.205	-0.098
$log(Trad\_value)_{it}$	0.064***	0.022**	0.083***	0.023*
σ_{it}	9.959***	8.188***	11.291***	9.943***
$log(NT)_{it}$	-0.373***	-0.198***	-0.484***	-0.274***
$log(price)_{it}$	-0.499***	-0.538***	0.014	-0.042***
$\|OIB_{it}\|$	0.294***	0.261***	0.482***	0.500***
Mon_{it}	0.016	-0.045*	-0.021	-0.078***
Thu_{it}	0.013	-0.007	-0.003	-0.021
Thr_{it}	0.011	-0.018	-0.004	-0.031
Fr_{it}	0.01	-0.008	-0.01	-0.027
Constant	-0.840***	0.03	-5.217***	-4.106***
No. of Observations	9565	9565	9565	9565
R^2	0.234	0.098		

This table presets the results from two approaches of panel data model to test for the relation between liquidity and its determinants. (A) represents fixed effects model in which null hypothesis from Hausman test was rejected. (B) represent a linear regression model with panel-corrected errors to avoid cross- sectional dependence. The liquidity measures are *Bid-Ask_Spread* and *Eff_Spread*, defined in (2) and (1) respectively. *Trad_value* is the average of the daily traded value in local currency. σ is measured for each day (t) as $\sigma_t = log(HighPrice_t) - log(LowPrice_t)$. The absolute value of the order imbalance ($|OIB|$) is measured as the standardized difference by number of transactions between buys and sells. *Return* is computed with the daily close to close prices. $log(NT)$ is the log of the number of transactions. $log(price)$ is the daily closing price. Mon_{it}, Thu_{it}, Thr_{it}, Fr_{it} are the respective days-of-the-week dummy variables, the dummy for Wednesday is omitted. ***, **, and * denote significance at the 0.01, 0.05, and 0.10 levels, respectively.

Table 7: Orthogonalized Impulse-response function from a PVAR

Response Variable	Impulse Variable					
	(1)	(2)	(3)	(4)	(5)	(6)
	News	$\lvert OIB \rvert$	r	$log(NT)$	$log(Trad\_value)$	σ
$\lvert OIB \rvert$						
$p = 0$	0.001	0.199***	NA	NA	NA	NA
$p = 1$	0.002	0.007***	-0.001	-0.014***	-0.013**	-0.001
$p = 2$	0.000	0.001**	0.000	-0.005***	-0.006***	-0.001
Return						
$p = 0$	0.000	-0.001**	0.024***	NA	NA	NA
$p = 1$	0.000	0.000	0.003**	0.001	0.000	0.000
$p = 2$	0.000	0.000	0.000	0.000	0.000	0.000
$log(NT)$						
$p = 0$	0.009	-0.213***	0.048***	0.723***	NA	NA
$p = 1$	0.030***	-0.048***	0.017*	0.233***	0.133***	0.071***
$p = 2$	0.011***	-0.016***	0.004	0.076***	0.072***	0.039***
$log(Trad\_value)$						
$p = 0$	0.006	-0.254***	0.045***	0.830***	0.691***	NA
$p = 1$	0.031**	-0.038**	0.025**	0.214***	0.339***	0.065***
$p = 2$	0.010*	-0.010	0.030**	0.054***	0.124***	0.030**
σ						
$p = 0$	0.001***	-0.003***	-0.001***	0.005***	0.000	0.016***
$p = 1$	0.000*	-0.001***	-0.001	0.003***	0.000	0.005***
$p = 2$	0.000*	0.000***	0.000	0.001***	0.000	0.002**
$log(Bid\text{-}Ask\_Spread)$						
$p = 0$	0.015**	0.075***	-0.001***	-0.151***	0.045***	0.127***
$p = 1$	-0.003	0.028***	-0.004	-0.095***	-0.022	0.037***
$p = 2$	-0.003	0.011***	-0.003	-0.043***	-0.025***	0.007
$p = 3$	-0.002*	0.004***	-0.001	-0.017***	-0.014***	0.000

This table reports results from the orthogonalized impulse-response functions. Variables on the top row are the impulses. The variables presented in the first column are the responses to the shocks. Each response presents spillover effects over 2 periods after the shock. The liquidity measure, *Bid-Ask_Spread,* is defined in (2). *Return* is computed with the daily close to close prices. $log(Trad\_value)$ is the average of the daily traded value in local currency. σ is the intraday volatility measured for each day (t) as $\sigma_t = log(HighPrice_t) - log(LowPrice_t)$. $log(NT)$ is the log of the number of transactions. The absolute value of the order imbalance ($\lvert OIB \rvert$) is measured as the standardized difference by number of transactions between buys and sells. $News_{it}$ is the dummy for days with presence of news releases. Note: .***, **, and * denote significance at the 0.01, 0.05, and 0.10 levels, respectively.

Table 8: Panel Data Regressions of Liquidity

Dependent Variable:	*log*(*Bid-Ask_Spread*)					
	(1)	(2)	(3)	(4)	(5)	(6)
$Return_{it}$	0.126	0.040	0.128	0.172	0.123	0.124
$log(Trad\_value)_{it}$	0.053***	0.053***	0.054***	0.054***	0.053***	0.053***
σ_{it}	10.545***	10.541***	10.564***	12.670***	10.670***	10.592***
$log(NT)_{it}$	-0.362***	-0.362***	-0.362***	-0.370***	-0.356***	-0.362***
$log(price)_{it}$	-0.511***	-0.511***	-0.511***	-0.514***	-0.505***	-0.509***
$\vert OIB_{it}\vert$	0.274***	0.274***	0.274***	0.282***	0.274***	0.243***
$News_{it}$	0.027*	0.027*	0.121	0.146***	0.185***	-0.136***
$Return * News_{it}$	-	0.261	-	-	-	-
$log(Trad\_value) * News_{it}$	-	-	-0.008		-	-
$\sigma * News_{it}$	-	-	-	-5.687***	-	-
$log(NT) * News_{it}$	-	-	-	-	-0.053***	-
$\vert OIB\vert * News_{it}$	-	-	-	-	-	0.259***
No. of Observations	12235	12235	12235	12235	12235	12235.000
R^2	0.321	0.321	0.321	0.324	0.324	0.322

This table reports results from panal data model to test for the interaction effects between each liquidity determinant and news as indicated in Equation 5. Column (1) represent the case base model of liquidity and from column (2) to column (6) show individual regression for each interaction. *Bid-Ask_Spread* is defined in (2). *Return* is computed with the daily close to close prices. $log(Trad\_value)$ is the average of the daily traded value in local currency. σ is the intraday volatility measured for each day (t) as $\sigma_t = log(HighPrice_t) - log(LowPrice_t)$. $log(NT)$ is the log of the number of transactions. $log(price)$ is the daily closing price. The absolute value of the order imbalance ($\vert OIB\vert$) is measured as the standardized difference by number of transactions between buys and sells. $News_{it}$ is the dummy for days with presence of news releases. The day-of-the-week dummy variables are included in the regression but they are not presented in the table because of the low significance as can be seen in Table 6. Hausman test was used to define the choice between random or fixed effects model. Null hypothesis was rejected for all regressions, then we use fixed effects model. ***, **, and * denote significance at the 0.01, 0.05, and 0.10 levels, respectively.

Table 9: Orthogonalized Impulse-response function from a PVAR, effects of interactions

Response Variable	Impulse Variable:		
	$News * \lvert OIB \rvert$	$News * log(NT)$	$News * \sigma$
$log(Bid\text{-}Ask\_Spread)$			
$p = 0$	0.018***	-0.031***	-0.028***
$p = 1$	0.015**	-0.027***	-0.012**
$p = 2$	0.004*	-0.012***	-0.004*
$p = 3$	0.001	-0.004**	-0.002*
$p = 4$	0.000	-0.002	-0.001
$p = 5$	0.000	-0.001	0.000

This table presents the interaction effects (between liquidity determinantsand news releases) on liquidity using orthogonalized impulse-response functions. Variables on the top row are the impulses. The variable presented in the first column is the response on liquidity to the interaction shocks. These responses presents spillover effects over 3 periods after the shock. *Bid-Ask_Spread* is defined in (2). σ is the intraday volatility measured for each day (t) as $\sigma_t = log(HighPrice_t) - log(LowPrice_t)$. $log(NT)$ is the log of the number of transactions. The absolute value of the order imbalance ($\lvert OIB \rvert$) is measured as the standardized difference by number of transactions between buys and sells. *News* is the dummy for days with presence of news releases. ***, **, and * denote significance at the 0.01, 0.05, and 0.10 levels, respectively.