North American Journal of Economics and Finance 50 (2019) 100997

Contents lists available at ScienceDirect

North American Journal of Economics and Finance

journal homepage: www.elsevier.com/locate/najef

How does information disclosure affect liquidity? Evidence from an emerging market

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ARTICLE INFO

JEL classification:
G10
G15
G19

Keywords:
Asymmetric information
Emerging markets
Informed trading
Liquidity
News releases

ABSTRACT

Cross-sectional models positively relate firm information disclosure with stock liquidity, but dynamic models on days of news releases show the opposite relation. We investigate this relationship by studying the effects of information disclosure on liquidity and its determinants. We use trade and quote data from Colombia for 2015 and 2016, along with a complete database of news releases as reported by firms to the regulator. The results of panel data and panel vector autoregressive (PVAR) models suggest that news releases increase both informed and uninformed trading. Overall, the negative effect of news releases on liquidity is temporary and fully explained by increasing asymmetric information.

1. Introduction

Firms have incentives to improve the market quality of their listed securities through increasing their disclosure of information. Among other things, this should lead to reductions in the cost of capital and liquidity risk (Diamond & Verrecchia, 1991). However, some empirical evidence, at odds with this theoretical prediction, reports that liquidity falls on days when information is disclosed (Koski & Michaely, 2000; Krinsky & Lee, 1996). This drop in liquidity in news days has been explained as higher adverse selection cost for the liquidity providers, since informed traders should be more active around those days.[1]

However, the interactions between information, trading activity and liquidity are not trivial. Liquidity is endogenous in the trading process, forming simultaneously with other trading variables, such as returns, volatility, and trading activity, which in turn are also affected by news releases (Grob-Klubmann & Hautsch, 2011; Riordan, Storkenmaier, Wagener, & Zhang, 2013). Because of the bidirectional effects between the trading variables, it is not clear how these variables interact to decrease liquidity in days of news. To investigate this, we study how the disclosing of information on days of new releases affects both liquidity and its determinants.

We use the Colombian stock market as a case study for two reasons. First, the issues of liquidity and information are particularly important for the development of emerging markets[2]. Due to its size and development, Colombia is usually classified as a small or secondary emerging market, with some similarities with frontier markets (FTSE, 2017; MSCI, 2016). Arguably, liquidity-related constraints should be more critical in these markets that in those in the verge of becoming developed ones, as Korea and Taiwan.

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[1] According to the models of Holthausen and Verrecchia (1990) and Kim and Verrecchia (1994), disclosures should increase the activity of informed traders, as they seek to exploit their private information, before and on the announcement day.

[2] The literature in Emerging Markets have reported that poor levels of liquidity have negative effects on volatility (Rhee & Wang, 2009), foreign investment (Chuhan, 1992), financial integration (Bekaert & Harvey, 1995), and returns (Lesmond, 2005).

https://doi.org/10.1016/j.najef.2019.100997
Received 28 November 2018; Received in revised form 4 April 2019; Accepted 30 May 2019
Available online 08 June 2019
1062-9408/

Moreover, the case of Colombia is representative of stock markets structured as a pure limit order book market, without designated market makers, as most emerging markets are (Wyman, 2016).

Second, we take advantage of a first-hand source of information: the database of firm announcements to the Superintendencia Financiera (SF), the Colombian financial regulatory agency. By law, Colombian public firms must report material information as soon as possible to the SF before to any news outlets. Typically, the information is reported electronically to the SF and soon thereafter learned by news companies and traders from the SF database. We choose Colombia because of its availability of high-quality data and its strict procedures on disclosing information for listed stocks as well as its corporate governance standards and straightforward channels for firms' announcements[3]. In this respect, we are confident on having almost all the official news associated to the firms in the sample, with the time they are made public. Other studies might be limited for using news releases on companies from specific business sources, such as Yahoo! Finance and Raging Bull (Antweiler & Frank, 2004), the *Wall Street Journal* (Tetlock, 2010), and Thomson Reuters (Grob-Klubmann & Hautsch, 2011; Riordan et al., 2013). Moreover, we take advantage of a trade and quote database available for the Colombian stock market that allows us to calculate intraday measures of liquidity, rather than to use liquidity proxies[4].

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 recognize that trading characteristics are jointly determined (Roll, 1984; Kyle, 1985; Glosten & Milgrom, 1985; Easley & O'Hara, 1992; Hasbrouck, 1995). Consequently, we run panel vector autoregressive (PVAR) models to account for this endogeneity. Several recent papers have used PVAR to capture dynamic interdependence among endogenous variables in a panel data setting, but to our knowledge, this is the first to do so to model liquidity.[5]

Accordingly, we contribute to the literature by testing the interaction between liquidity and its determinants, overall and on the days of news releases. Thus, we can confirm the temporary negative relationship between liquidity and news and find the associated channels. Most importantly, our results show that the drop in liquidity on news days is sufficiently explained by increasing information asymmetry. To our knowledge, this has not been reported by the literature but agrees with the implications of the classical models of adverse selection effects on liquidity (Kyle, 1985; Glosten & Milgrom, 1985; Easley & O'Hara, 1987). In this way, we shed light on how information is incorporated into prices in the trading process, particularly on days when information is made public. Besides, the results of this study serve as an out-of-sample test of some theoretical models and empirical findings in market microstructure, most of which come from developed stock markets (Grob-Klubmann & Hautsch, 2011; Tetlock, 2010; Riordan et al., 2013).

Our main results can be summarized as follows. We find that volatility, the number of trades, and information asymmetry have distinctive effects on liquidity on news days, as indicated by their marginal effect on those days. First, a lower marginal effect of volatility on news days helps to improve liquidity, rather than decrease it. Second, both the total and marginal effects of the number of transactions on liquidity are positive. Thus trading activity improves liquidity overall, all the more so on the day of news releases. Third, both the total and marginal effects of order imbalances on liquidity are negative, which is consistent with the implications of theoretical models on the effect of information asymmetry on liquidity (Easley & O'Hara, 1992; Glosten & Milgrom, 1985; Kyle, 1985). Moreover, after controlling for this marginal effect, we find that liquidity improves on news days. In other words, the increasing information asymmetry on news days sufficiently explains the drop in liquidity. According to the theoretical models, news releases attract both informed and noise traders, the net effect is an increase in trading activity and volatility but a reduction in liquidity. In sum, our evidence suggests that although news releases reduce liquidity temporarily, creating an information asymmetry effect, overall they have a beneficial effect on liquidity.

The studies most closely related to ours are those of Grob-Klubmann and Hautsch (2011) and Riordan et al. (2013), who investigate the impact of news on microstructure characteristics using vector autoregressive (VAR) models to examine the London Stock Exchange and the Toronto Stock Exchange, respectively. We have three main differences with these studies. First, we study the interactions between liquidity determinants and news releases, in order to observe the incremental effects on these variables on days when information is announced. Second, we study data from an emerging market, a particularly interesting subject of study, because it has lower liquidity and presumably larger information asymmetry than developed markets[6]. Third, we use PVAR models. Like panel data models, the PVAR approach allows us to study contemporaneous reactions to news, liquidity determinants, and interactions, giving more efficient estimates than time-series models by stock. Moreover, the PVAR provides more robust results by controlling for the dynamics among the variables and for the endogeneity

[3] Firms listed on the Colombian stock market must comply with the provisions in corporate governance regulation 275, in terms of a timely, complete and truthful information disclosure. (República de Colombia, 2001).

[4] Liquidity has been little studied in emerging markets, mostly for the lack of trading and quote data (Fong et al., 2017). In fact, some recent studies in liquidity of emerging markets still use daily proxies such as the Amihud Ratio (Syamala, Wadhwa, & Goyal, 2017; Chauhan, Kumar, & Pathak, 2017), the closing quote spread (Chung & Wang, 2016; Liew, Lim, & Goh, 2018) or both (Lee & Chung, 2018; French & Taborda, 2018).

[5] Some recent studies that use PVAR models are Love and Zicchino (2006), which investigates the relationship between a firm's investment decisions and financial development at the corporate level; Grossmann, Love, and Orlov (2014), which studies the interactions between foreign exchange volatilty and macroeconomic and financial variables at the country level; Galariotis, Makrichoriti, and Spyrou (2016), which researches the spillover effects from a financial crises in sovereign credit default swap (CDS) spreads; and, finally, Mcgregor (2017), which measures macroeconomic responses to price shocks in global commodities.

[6] For example, Agudelo, Giraldo, and Villarraga (2015) measure information asymmetry in six Latin American emerging markets, using the Dynamic PIN Measure of Easley, Engle, O'Hara, and Wu (2008). They find that in average, Colombia has lower liquidity and similar or higher information asymmetry than Mexico and Brazil, the two most developed markets in the region.

between them[7].

The rest of this paper is organized as follows. Section 2 gives 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 those in Easley and O'Hara (1992), Glosten and Milgrom (1985), and Kyle (1985)—postulate that informed trading increases the cost of adverse selection 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/or price impacts to mitigate their losses. Diamond and Verrecchia (1991) broadens this theory by including the effect of information disclosure. They posit that information announcements, by mitigating adverse selection costs, attract large demand by investors (e.g., institutional traders) and reduce a firm's cost of capital. Cross-sectional studies provide empirical support for the theoretical negative relationship between information asymmetry and the firm's information disclosure. Brown and Hillegeist (2007) and Sankaraguruswamy, Shen, and Yamada (2013) find that firms with higher-quality disclosure have lower levels of information asymmetry over the long run.

However, the existing literature on dynamic models is not entirely consistent with the above mentioned results. Koski and Michaely (2000) and Krinsky and Lee (1996) report higher adverse selection cost components in 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 news events. In contrast, informed traders should react more rapidly to exploit their advantage (Kim & Verrecchia, 1994). In the same vein, Riordan et al. (2013) show that releases of negative news reduce liquidity at the time of disclosure, by increasing the cost of adverse selection.

From the previous discussion, we expect that the presence of news would generate information asymmetry and reduce liquidity. Moreover, some other trading characteristics are also affected by the incoming 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 is announced. Kim and Verrecchia (1994) argue that trading volume rises at the time of earnings announcements. They suggest that the increase in trading activity comes, at least in part, from informed trading[8].

2.2. Liquidity determinants

The market microstructure literature also discusses the relations among the trading variables that are determinants of liquidity: volatility, trading activity, order imbalance, and returns. Extensive literature shows a positive relation between trading activity (traded volume or number of trades) and volatility, including Downing and Zhang (2004), Jones, Kaul, and Lipson (1994), Karpoff (1987), and Wang and Wu (2015). From the perspective of information, news releases lead to disagreements among traders, which causes trading prices to move more erratically. In turn, Chordia, Roll, and Subrahmanyam (2002) report, at the market level, a negative relationship between the absolute value of order imbalance and trading activity. They also argue that order imbalance is related to price declines because of the temporary inventory imbalances when prices drop quickly. Some evidence also indicates that positive stock returns reduce inventory costs for liquidity providers, resulting in narrower spreads (Chordia, Sarkar, & Subrahmanyam, 2005).

Two reasons emerge for the strong positive relationship between volatility and bid-ask spreads. First, inventory cost models (Stoll, 1978; Ho & Stoll, 1981) imply that higher volatility levels represent an increased risk of an adverse price change for market makers. Second, Roll (1984) model makes explicit the strong link between the bid-ask bounce and intraday volatility. Empirical studies, such as Chordia et al. (2005) and Watanabe (2004), confirm this negative relation between volatility and liquidity at the market level.

Other empirical studies report a positive relationship between trading activity and liquidity (Watanabe, 2004; Lesmond, 2005; Stoll, 2000). For liquidity providers, more frequent trading mitigates the risk of not finding counterparties to balance their positions (Ho & Stoll, 1981). Additionally, larger trading activity can be positively related to a lower adverse selection cost, and improved liquidity, when implies a larger proportion of uninformed traders (Easley & O'Hara, 1992; Easley, Kiefer, O'Hara, & Paperman, 1996).

3. Data

We use a trade and quote database collected from Bloomberg, from January 2, 2015, to November 22, 2016.[9] This contains

[7] Unlike panel data regressions, the PVAR model accounts for the endogeneity between the trading variables: return, volatility, trading activity, and liquidity. This is particularly important for our purposes: Since liquidity, trading activity and volatility are persistent in daily frequency and theoretically affect one another over time, any effect of an exogenous variable on liquidity could be clouded by the effects of its own lags or the lags of trading activity or volatility if they were not controlled for.

[8] Other studies that report a link between news and both volatility and trading activity are Grob-Klubmann and Hautsch (2011), Hautsch (2008), Kalev et al. (2004) and Karpoff (1986).

[9] Bloomberg stores only six months of intraday data, so this dataset had to be manually downloaded four times over two years.

intraday data for 42 companies listed on the Colombian stock market.[10] Trades and quotes are time-stamped at the second. We omit trades from our sample that occurred in volatility call auctions and closed call auctions, to focus only on the continuous market.[11]

We collect data on news releases for listed companies from the website of the financial regulatory agency Superintendencia Financiera (SF), which publishes firm announcements in real time. The issuers of securities are required to communicate relevant information[12] (República de Colombia, 1995), which must be disclosed by the issuer immediately after material new information appears, no matter if originated internally or from a third party. After the information is reviewed and published on the SF website, it becomes available to the media and the general public. Thus, the time stamp of publication, as appears in the news release database, shows the hour and the day that the information is released to the market[13]. Table A1 in the Appendix, shows the information categories in the data. Press releases and the organizational structure categories represent up to the 50% of the news data. Organizational structure relates to corporate changes or events related to its economic activity. Other important news categories are accounting adjustements (22.2%), credit score changes (8.0%) and meetings of shareholders (6.3%).

3.1. Liquidity measures

We use two measures to describe daily effective illiquidity. The first measure is the effective spread—as in Fong, Holden, and Trzcinka (2017) and Goyenko, Holden, and Trzcinka (2009)—a widely-used liquidity benchmark, based on intraday data.

$$Eff\_Spread_\tau = 2|log(P_\tau) - log(M_\tau)| \tag{1}$$

where P_τ is the trading price in transaction τ, and M_τ is the midpoint in the bid-ask spread before the trade is completed. The daily effective spread Eff_Spread_t is the average of this measure computed for all trades in a day t.

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

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

Ask_τ is the prevailing best-ask price, Bid_τ is the prevailing best-bid price before the transaction τ, and M_τ is the midpoint average between the two. The daily quoted bid-ask spread ($Bid\text{-}Ask\_Spread_t$) is the average of the bid-ask spreads computed for all trades in a day t.

3.2. Liquidity determinants

We calculate the following daily liquidity determinants from the intraday database: daily return, daily trading value, intraday volatility, number of trades, closing price, and order imbalance.[14] Previous studies use these trading characteristics as control variables to model liquidity in panel data or VAR settings (Agudelo et al., 2015; Grob-Klubmann & Hautsch, 2011; Grullon, Kanatas, & Weston, 2004; Lesmond, 2005; Riordan et al., 2013).

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

$$\sigma_{it} = log(HighPrice_{it}) - log(LowPrice_{it}) \tag{3}$$

These authors report that the daily range is a highly efficient estimator of volatility and avoid the limitations of stochastic volatility models, generalized method of moments and likelihood-based estimation through numerical integration. Recent papers—such as Chiang and Wang (2011), Wang (2007), Wang and Wu (2015), and Agudelo, Byder, and Yepes-Henao (2019)—use this volatility measure.

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

$$|OIB_{it}| = |Buys_{it} - Sells_{it}| /NT_{it} \tag{4}$$

[10] We exclude 17 securities from the sample. First, we drop stocks with insufficient intraday transactional information, less than three transactions per day. Second, we take care of dual-class stocks, leaving only the most traded share.

[11] Volatility call auctions last two to three minutes and are triggered by large variations in trading prices. Closing call auctions are scheduled for the last five minutes of the trading day. We identify volatility call auctions using a proprietary database from the Colombian stock exchange Bolsa de Valores de Colombia.

[12] The Decree 3139 of 2006 (República de Colombia, 2006) requires that the firm reveals any relevant information that may affect its listed securities. The information is classified depending on the origin as financial and accounting news, legal news, commercial and labor news, business crises and issuance of securities.

[13] The news days are defined according to the time of the news releases and the trading hours of the stock market. That is, if the news are issued before (after) the closing time, they are assigned to that (the next) trading day.

[14] Trading value is preferred to volume (number of traded shares) as a measure of trading activity because of the wide price variations across stocks in BVC, from 10 to 60,000 Colombian pesos (COP). Using volume would falsely equate a trade of 10 million shares for a stock at COP 20 per share with another trade for the same number of shares but for a stock with a price around COP 50.000.

where $|OIB_{it}|$ is the absolute value of order imbalance of the stock *i* for day *t*. $Buys_{it}$ are the number of buyer-initiated trades, $Sells_{it}$ are the number of seller-initiated trades, and NT_{it} is the total number of trades. We use the Lee and Ready (1991) algorithm to classify each trade as either buyer or seller-initiated.

4. Methodology

This section explains the econometric strategy used to estimate the interaction effects between news releases and liquidity determinants, based on both panel data and panel VAR models.

4.1. News effect on control variables and Liquidity: Panel data model

As a first approximation to the relation between liquidity and news, we regress a panel data model commonly used in the literature to model the bid-ask spread (Agudelo et al., 2015; Cesari, Espenlaub, & Khurshed, 2011; Grullon et al., 2004; Lesmond, 2005). We control for the liquidity determinants and include a news variable $News_{it}$ as a dummy with a value of one for stock days with news releases and zero otherwise. The equation model is given as follows:

$$Illiquidity_{it} = CtrlVbles_{it} + \delta_1 News_t + \delta_2 CtrlVble_j{}^{*}News_{it} + \varepsilon_{it}$$

$$CtrlVbles_{it} = \beta_1 r_{it} + \beta_2 log(NT_{it}) + \beta_3 log(Trad\_value_{it}) + \beta_4 \sigma_{it} + \beta_5 log(price_{it}) + \beta_6 |OIB_{it}| \quad (5)$$

where subscripts *i* and *t* represents the cross-section (stocks) and time-series (days) observations, $Illiquidity_{it}$ is alternately 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, $\log(Trad\_value_{it})$, the logarithm of daily trading value, σ_{it} the intraday volatility defined in Eq. (3), $\log(price_{it})$ the log of the closing price, and $|OIB_{it}|$ the order imbalance measure. We include both the trading value and the number of trades as trading activity variables, to account indirectly for the average size of the orders. $CtrlVble_j * News_{it}$ represents interactions between the news variable and each of the liquidity determinants. Finally, We run [5] using the Panel-Corrected Standard Errors (PCSE) model by Beck and Katz (1995). This model corrects for the contemporaneous correlation, temporal dependence y panel heteroscedasticity of errors, likely to appear on the long panels ($T > N$).

4.2. News effect on control variables and Liquidity: Panel VAR

We use the PVAR model with fixed effects to model the interactions between trading variables on news days, providing a more robust set of results than those of the traditional panel data approach.[15] Again, the main advantage of the PVAR model over traditional panel data regression is that it treats all variables as endogenous. The PVAR model captures dynamic interdependence between liquidity and its determinants by including their lags. Besides, by including fixed effects, this model allows us to account for cross-sectional unobserved heterogeneities among stocks. Finally, it also allows for time dummies that can capture systematic liquidity effects (Chordia, Roll, & Subrahmanyam, 2000; Huberman & Halka, 2001). The one-lag panel VAR model in reduced form can be written as follows:

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

where subscripts *i* and *t* represents individual stocks and days, respectively, Y_{it} is the vector of endogenous variables for stock *i*, *A* is a matrix of autoregressive coefficients for lag one, f_i is a vector of fixed effects that captures unobservable firm-specific levels, and d_t is a dummy variable to capture common time effects.[16]

We select one lag as the optimal autoregressive order for our system using the Akaike, Schwarz, and Hanan and Quinn information criteria. To order the variables from the least to the most endogenous, as required by the PVAR methodology, we start with theoretical considerations. The dummy news variable, representing days when the firm releases information, has to be the most exogenous one, for not depending on the trading process. Next, we place the order imbalance, proxy for asymmetric information, assuming that it appears after information is released. Then, we put stock returns, assuming that prices adjust to the directional trades almost immediately. 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.

Finally, in alternative PVAR models, we interact our news dummy variable with each liquidity determinant. Our interactions are located in the vector *Y* after the two variables interact to maintain the same ordering of the Cholesky procedure. As in the panel data

[15] We are indebted to Love and Zicchino (2006) for developing the PVAR model procedure for the statistic software STATA.

[16] Because the explanatory variables are lags of the dependent variables, time-invariant factors are correlated with regressors. Thus, the first-difference procedure 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. Eq. (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 in the error term *eit*. 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 *eit* (see Hamilton, 1994). Then, we replace time dummies *dt* by subtracting the cross-sectional mean from each variable in the system, following Berdiev and Saunoris (2016), Grossmann et al. (2014), and Hristov and Hulsewig, Wollmershauser (2012). This procedure is equivalent to maintaining the dummies in the model.

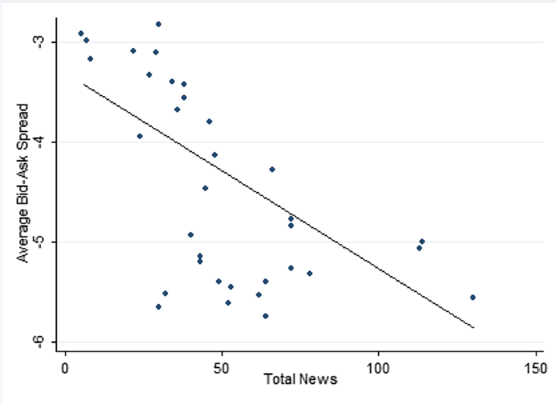

Fig. 1. Liquidity and News releases across firms. The figure shows a scatter plot between the averages of the *Bid-Ask_Spread* with respect to total number of news published over the sample time (Between January of 2015 and November of 2016). Each point represents one company, and there is a total of 34 companies with news reported.

model, we run a different regression for each interaction term in order to avoid overidentification.

5. Descriptive statistics

We present descriptive statistics to compare the relationship of liquidity to news releases in both cross-sectional and time-series approaches. Fig. 1 shows the relationship between total news releases and average liquidity for the stocks in the sample, and Table A2 in the Appendix lists data for each stock. This graph suggests that companies with more news releases tend be more liquid, i.e. have a lower daily average bid-ask spread. This is consistent with static studies (Brown & Hillegeist, 2007; Sankaraguruswamy et al., 2013) reporting that firms with more information disclosure attain higher liquidity levels, even after controlling for information asymmetry proxies, trading activity, and other market microstructure variables.

Table 1 shows the cross-correlations between pairs of characteristics. First, it confirms the negative correlation between total news and both illiquidity measures. It also presents the bivariate relationships between illiquidity measures and their determinants (columns 1 to 3). Liquidity appears to be positively and significantly related to trading activity (in both traded value and number of trades) and negatively related to the absolute value of order imbalance. This is consistent with market microstructure theories suggesting that informed trading, proxied by imbalances in the order flow, decreases liquidity because of the increasing adverse selection cost for liquidity providers (Easley & O'Hara, 1992; Glosten & Milgrom, 1985). As in the previous analysis, higher volatility levels also increase liquidity provider costs, which results in wider bid-ask spreads (Stoll, 1978; Ho & Stoll, 1981). Finally, empirical studies such as Lesmond (2005) and Stoll (2000) explain the positive relationship between trading activity and liquidity with inventory costs. From the microstructure perspective, trading activity reflects not only information release but also different

Table 1
Pooled Cross-sectional Correlations.

Variable	*Log (Bid-Ask_spread)* (1)	ln (*Avg_spread*) (2)	ln (*Eff_Spread*) (3)	log (*Trad_value*) (4)	σ (5)	|*OIB*| (6)	*OIB* (7)	*Return* (8)	log(*NT*) (9)
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				
|*OIB*|	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

This table reports the correlation between the averages of trading variables across the 34 stocks. The liquidity measures are: *Bid-Ask_Spread* defined in Eq. (2), *Avg_spread*, which is the bid-ask spread averaged by volume and the *Eff_Spread* defined in Eq. (1). Other variables are: log(*Trad_value*), the average of the daily traded value in local currency; and σ, 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 (|*OIB*|) 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 news releases. ***, **, and * denote significance at the 0.01, 0.05, and 0.10 levels, respectively.

Table 2
Descriptive Statistics: Dynamic Analysis.

	(A): Day-1 to news release		(B): Day of news release		(B) – (A)
	Mean	Std. Dev	Mean	Std. Dev	
log(*Bid-Ask_Spread*)	−5.018	0.026	−5.001	0.026	0.0168
log(*Trad_value*)	12.132	0.059	12.146	0.059	0.015
σ	0.0203	0.001	0.022	0.001	0.001
ln(*NT*)	3.010	0.042	3.039	0.042	0.028
$\lvert OIB\rvert$	0.607	0.007	0.609	0.007	0.003
Return	0.000	0.001	−0.001	0.001	0.000
No. of Observations	1143		1143		

Note: (A) represents the day previous to the news disclosure day, (B) represents the day of the news disclosure. The last column shows the difference between (A) and (B). t-test is used to compare the statistical significance of these results. *Bid-Ask_Spread* is defined in Eq. (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 ($|OIB|$) is measured as the standardized difference by the 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.

interpretations of that information and the presence of noise trading. Anderson (1996) supports this theory by revealing that a substantial part of daily volume is unrelated to information disclosure. Thus, trading activity is largely noisy and associated with high volatility but not necessarily to information asymmetry.

Next, we compare the behavior of variables on news release days and on the previous day with the same stock. Table 2 suggests that illiquidity and volatility increase from days with no news to days with news. There are also increases in the average of the two trading activity variables and the absolute value of order imbalance, a proxy for informed trading. These results are already suggested by the last row of Table 1, that shows that the news release dummy has significant positive correlations with the three bid-ask spreads, traded value, volatility, and the proxy for informed trading.

Table A3 in the Appendix shows the results of the Cholesky variance decomposition at stock-level, a prerequisite of the PVAR model. We chose the following exogeneity order as the most predominant for the stocks in the sample: News variable, order imbalance, return, the number of trades, trading volume, volatility and liquidity. [17]Since the results do not indicate the same exogeneity order for each stock, as a robustness test of the main results, we invert the order in the PVAR of the four most endogenous variables, which are jointly determined in the trading process: return, the number of trades, trading value, and volatility.

In summary, the preliminary evidence suggests that firms with more frequent information disclosure have higher levels of liquidity. This is consistent with theoretical approaches and cross-sectional studies that indicate that these companies have lower information asymmetry and liquidity risks and therefore a lower cost of capital and higher liquidity (Brown & Hillegeist, 2007; Diamond & Verrecchia, 1991; Sankaraguruswamy et al., 2013). However, the information at the time of disclosure appears to have an immediate adverse effect on liquidity, consistent with previous time-series studies (Koski & Michaely, 2000; Krinsky & Lee, 1996; Riordan et al., 2013).

6. Results

This section discusses the results of two alternative approaches to model the relationship between liquidity determinants and the effect of news releases. We start with the results of panel data regressions in each of the two liquidity proxies in Table 3. Panel A reports the results of fixed-effect models, and Panel B those of a model with panel-corrected errors to avoid cross-sectional dependence. These results support the findings of the descriptive statistics discussed above[18]. 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 expectations, is negatively related to stock liquidity. This appears to be simply the consequence of controlling for the number of trades, leaving the trading value just as a measure of daily average size of trades. Trade size is related to informed trading (Easley & O'Hara, 1987) and the price impact of large orders

[17] Table A3, in the appendix, summarizes the results, showing the proportion of self-explained variance for each variable for the tenth period ahead, averaged across stocks. A higher proportion identifies a more exogenous variable. The results show that in 75% of the stocks the news variable is the most exogenous. Thus we keep this variable in first place. $|OIB|$ and stock returns are equally likely to be in second place, but, we assume $|OIB|$ to be the most exogenous, as directional trading should precede price formation. Then, the number of trades is always below stock returns. The trading value presents low proportion of self-explained variance, but we keep it right after log(*NT*) as another trading activity variable. Moreover, in 96% of the stocks volatility has a lower proportion of self-explained variance that the number of trades, and in 63% of the stocks, higher than illiquidity. Finally, the last row in the table shows the average of the proportion of self-explained variance and supports the ordering of endogeneity of the variables mentioned above.

[18] In omitted results, we run two alternative models more appropriate to deal with long panels ($T > N$): the pooled mean group and the mean group models. The results are qualitatively the same.

Table 3
Panel data regressions of liquidity.

Model:	(A)		(B)	
Dependent Variable:	log(*Bid-Ask_Spread*)	log(*Eff_Spread*)	log(*Bid-Ask_Spread*)	log(*Eff_Spread*)
Return	0.183	−0.073	0.205	−0.098
log(*Trad_value*)	0.064***	0.022**	0.083***	0.023*
σ	9.959***	8.188***	11.291***	9.943***
log(*NT*)	−0.373***	−0.198***	−0.484***	−0.274***
log(*price*)	−0.499***	−0.538***	0.014	−0.042***
$\|OIB\|$	0.294***	0.261***	0.482***	0.500***
Mon	0.016	−0.045*	−0.021	−0.078***
Thu	0.013	−0.007	−0.003	−0.021
Thr	0.011	−0.018	−0.004	−0.031
Fr_i	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 shows the results from two approaches of the panel data model to test for the relation between liquidity and its determinants. (A) represents a fixed-effects model in which the null hypothesis from the Hausman test was rejected. (B) represents 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 Eqs. (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*, *Thu*, *Thr*, *Fr* are the respective day-of-the-week dummy variables, in which the dummy for Wednesday is omitted. ***, **, and * denote significance at the 0.01, 0.05, and 0.10 levels, respectively.

(Madhavan, 2000). Similar relationships are reported in the US market by Downing and Zhang (2004), Ozsoylev and Takayama (2010), and Wang and Wu (2015).

6.1. Liquidity determinants and news releases

Table 4 reports results from the orthogonalized impulse response functions (OIRF) up to three periods ahead. The OIRF's are estimated from PVAR model (6) as the incremental effect on each variable in the row over time following an orthogonalized shock to the variable in the column.

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 news release day. This partially agrees with Riordan et al. (2013), who find the same effect for negative news but not for neutral or positive news. In the last row in Table 4, the effects of shocks of the trading variables on liquidity also appear significant and with the sign reported in Table 3. The effects of order imbalance, a proxy for informed trading, and the number of trades appear statistically significant even after three days.

In addition, news releases have a positive effect on volatility, and this response is still significant after three days. This is consistent with the findings of Kalev et al. (2004), who report a time dependence of volatility at the rate of the public information release. The news releases also have a positive impact on trading activity, measured by trading value and the number of trades. This is consistent with the argument by Chordia, Roll, and Subrahmanyam (2001) that announcements induce more trading activity by attracting both informed and uninformed traders. The news releases are also positively related to the asymmetric information proxy ($|OIB|$). This supports the notion that news is informative to the market and that at least part of the increase in trading reflects the activity of informed traders (Kim & Verrecchia, 1994; Koski & Michaely, 2000; Krinsky & Lee, 1996).

To complement the previous results, in columns 2–6 we examine the impulse-response among the trading variables. First, each variable shows clear persistence 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 (Kavajecz & Odders-White, 2001), which is often accounted for by autoregressive conditional heteroskedasticity regression models (GARCH).

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

In column 6, we present evidence of a negative relationship between volatility and liquidity, that is, volatility shocks lead to higher bid-ask spreads. This relationship is theoretically explained by inventory costs (Stoll, 1978; Ho & Stoll, 1981) and is also

Table 4
Orthogonalized Impulse-response function from a PVAR.

Response Variable	Impulse Variable					
	(1) *News*	(2) $\|OIB\|$	(3) *Return*	(4) log(*NT*)	(5) log(*Trad_value*)	(6) σ
$\|OIB\|$						
$p = 0$	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-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

This table reports results from the orthogonalized impulse-response functions. Variables in the top row are the impulses. The variables in co lumn 1 are the responses to the shocks. Each response shows spillover effects over two periods after the shock. The liquidity measure, *Bid-Ask_Spread,* is defined in Eq. (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) calculated 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 ($|OIB|$) is measured as the standardized difference by the number of transactions between buys and sells. *News* is the dummy for days with news releases.***, **, and * denote significance at the 0.01, 0.05, and 0.10 levels, respectively.

reported at the market level in the empirical findings of Chordia et al. (2005) and Watanabe (2004). Finally, we find a two-way positive relationship between trading activity and volatility, significant even after three days. This can be explained as new information attracting traders who might disagree about the meaning of the information (Karpoff, 1987), leading to price instability. In turn, more volatile stocks attracts trading activity, especially among day traders (Kyrolainen, 2008). Column 6 also shows that the effect of volatility on trading activity is persistent. They argue that this relationship comes from institutional investors' trading large volumes among themselves to reduce transaction costs.[19]

In summary, the results of PVAR model in Table 4 confirm the results of the effects on liquidity of the Panel data model in Table 3, controlling for the endogeneity and dynamic effects between the variables. As a bonus, the PVAR modelling offers a richer perspective of the interaction between the trading variables in a stock exchange.

6.2. Interactions between liquidity determinants and news releases

To investigate the mechanisms of the effect of news releases on liquidity, we examine the effects of the interactions between trading variables and news releases on the bid-ask spread. Table 5 shows the results from model [5] using PCSE. By including the interactions of the liquidity determinants with news day dummy variable, one at the time, we can measure their marginal effects on liquidity, on days of news releases, as shown in columns 1–6. Further, the coefficient of news in the base case regression (column 1) changes significantly after including some of the interactions.

In the case of volatility (column 4), the negative coefficient of its interaction with the news variables suggests that news releases reduce the positive effect of volatility on bid-ask spreads. Moreover, the news effect on liquidity becomes more negative and significant. We interpret this as that informed trading becomes more important in determining liquidity on news days, as explained below. Regarding the number of transactions (column 5), we find that its marginal effect on bid-ask spreads on news days is negative,

[19] Downing and Zhang (2004) also report a positive relation between trading activity and volatility, but in municipal bonds.

Table 5
Panel data Regressions of Liquidity with interaction.

Dependent Variable	log(*Bid-Ask_Spread*)					
	(1)	(2)	(3)	(4)	(5)	(6)
Return	0.198	0.193	0.200	0.241	0.194	0.194
log(*Trad_value*)	0.082***	0.082***	0.084***	0.085***	0.082***	0.082***
σ	11.221***	11.221***	11.233***	13.551***	11.345***	11.286***
log(*NT*)	−0.484***	−0.484***	−0.483***	−0.492***	−0.473***	−0.483***
log(*price*)	0.014	0.014	0.014	0.017	0.013	0.013
$\|OIB\|$	0.479***	0.479***	0.480**	0.490***	0.481***	0.428***
News	0.048**	0.048**	0.141	0.168***	0.227***	−0.176***
Return × *News*	–	0.013-	–	–	–	–
log(*Trad_value*) × *News*	–	–	−0.008	–	–	–
σ × *News*	–	–	–	−5.747***	–	–
log(*NT*) × *News*	–	–	–	–	−0.060***	–
$\|OIB\|$ × *News*	–	–	–	–	–	0.355***
No. of Observations	9565	9565	9565	9565	9565	9565

This table shows the results from the panel data model to test for the interaction effects between each liquidity determinant and news, as indicated in Eq. (5). We estimate the parameters using the PCSE model of Beck and Katz (1995). Column 1 is the base model of liquidity, and columns 2–6 show individual regressions for each interaction. *Bid-Ask_Spread* is defined in Eq. (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 ($|OIB|$) is measured as the standardized difference by number of transactions between buys and sells. $News_{it}$ is the dummy for days with news releases. The day-of-the-week dummy variables are included in the regression, but not presented. ***, **, and * denote significance at the 0.01, 0.05, and 0.10 levels, respectively.

as is the unconditional effect. In other words, the positive effect of trading activity on liquidity increases on the information release. 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 disclosures in trading variables.

The last column in Table 5 presents the interaction between order imbalance and news releases. This result indicates that order imbalance decreases liquidity and even more on news release days. This is expected, because the informed trading proxy, $|OIB|$, should be more correlated with information asymmetry on days of news releases. Also, interestingly, the negative coefficient in the news variable in column 8 suggests that $|OIB|$ completely reverses the isolated effect of news, subsuming the negative effect of the news on liquidity. This is confirming evidence of the validity of the order imbalance as a proxy for informed trading. We interpret this as that the drop in liquidity on news days can be sufficiently explained by our informed trading proxy, the absolute value of the order imbalance. As far as we know, this result has not been reported by the literature but is compatible with the implications of the theoretical models of the bid-ask spread in a continuous market with information asymmetries such as Glosten and Milgrom (1985) and Easley and O'Hara (1987).

Because liquidity determinants are caused simultaneously and the panel data approach does not account for this, we use PVAR model (6) with the inclusion of the same interactive variables, one at the time. Again, the PVAR approach provides a more robust set of results, by controlling for the dynamic behavior and bidirectional causality between the variables. Table 6 presents the estimates of

Table 6
Orthogonalized Impulse-response function from a PVAR, effects of interactions.

Response Variable	Impulse Variable		
log(*Bid-Ask_Spread*)	*News* × $\|OIB\|$	*News* × log(*NT*)	*News* × σ
$p = 0$	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

This table shows the interaction effects (between liquidity determinants and news releases) on liquidity using orthogonalized impulse-response functions. Variables in the top row are the impulses. The variable in column 1 is the response on liquidity to the interaction shocks. These responses show spillover effects over three periods after the shock. *Bid-Ask_Spread* is defined in Eq. (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 ($|OIB|$) is measured as the standardized difference by number of transactions between buys and sells. *News* is the dummy for days with news releases. ***, **, and * denote significance at the 0.01, 0.05, and 0.10 levels, respectively.

this model for the interaction effects on liquidity, validating the previous results. Order imbalances on news days reduce liquidity for up to two days afterward. This is further evidence that asymmetric information presented on days with news reduces liquidity more than on days with no news. In turn, the incremental negative effect of both trading activity and volatility on bid-ask spreads on news days is not only confirmed but appears to be significant up to three days afterward. In addition, PVAR allows us to measure the spillover effect over time after a contemporaneous shock. Overall, the OIRF results show that the temporary 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, trades and quotes collected from Bloomberg and firm news announcements from the Colombian financial regulatory agency. In 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 directly affect trading variables that determine liquidity but also modify their effect on liquidity. We have found that the marginal effect of volatility from news releases on illiquidity is negative, which is the opposite of the total effect. The marginal effect of the variable of the number of transactions on liquidity is negative and aligns with the total effect. More importantly, informed trading, proxied by the absolute value of order imbalance, increases its negative effect on liquidity on news days. Furthermore, it is the only trading variable that captures the negative total effect of news on liquidity. These results highlight the importance of news releases for liquidity and price formation in emerging markets, via informed trading, and not simply via inducing higher volatility and trading activity.

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

We leave for future research the study of the differential effects of classes of news on liquidity and trading variables. We might expect effects differing among positive, neutral or negative news, macro vs firm-specific news, or varying on the degree of surprise of the news, or the effect of the news on price. Those interactions can be better studied with the PVAR approach presented here. In addition, following a line of studies in emerging markets, the differential behavior of types of investors on news release days would be interesting, specifically, which types of investors are trading with information and which types provide liquidity.

Acknowledgments

This article originated with a thesis completed by the first author in partial fulfillment of requirements for a master of science in finance degree at Universidad EAFIT, under the guidance of the second author. We thank three anonymous referees for useful suggestions that helped us to improve this paper. We are also grateful to James Byder, Jesus Otero, and Diego Téllez-Falla for helpful discussions. We also thank Juliana Hincapié-Salazar for assembling the news release database. All errors remain the responsibility of the authors.

Appendix A

Table A1
Classification of News releases.

Concept	Number of News Releases	Participation
Organizational structure	878	28.1%
Press releases	869	27.8%
Accounting adjustments	695	22.2%
Credit Score	249	8.0%
Shareholder meetings	196	6.3%
Stock Issues and repurchases	149	4.8%
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).

Table A2
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
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
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
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
MINEROS	−3.947	0.905	−4.036	0.918	24

This table reports summary statistics of the liquidity variables and total news releases for each stock traded of the resulting sample of 24 companies. 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 Eqs. (1) and (2), respectively.

Table A3
Cholesky Variance Decomposition.

Nemo	*Percentage of own variance explained 10 periods ahead*						
	News	$\|OIB\|$	*Return*	log(*NT*)	log(*Trad_value*)	σ	log(*Bid-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 a long-run variance decomposition of the variables in the first row for each stock. Specifically, these results represent the percentage of variation in the variables explained by their own shocks for the tenth period ahead. *News* is a dummy for days with 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 trades 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 Eq. (2).

Appendix B. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.najef.2019.100997.

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