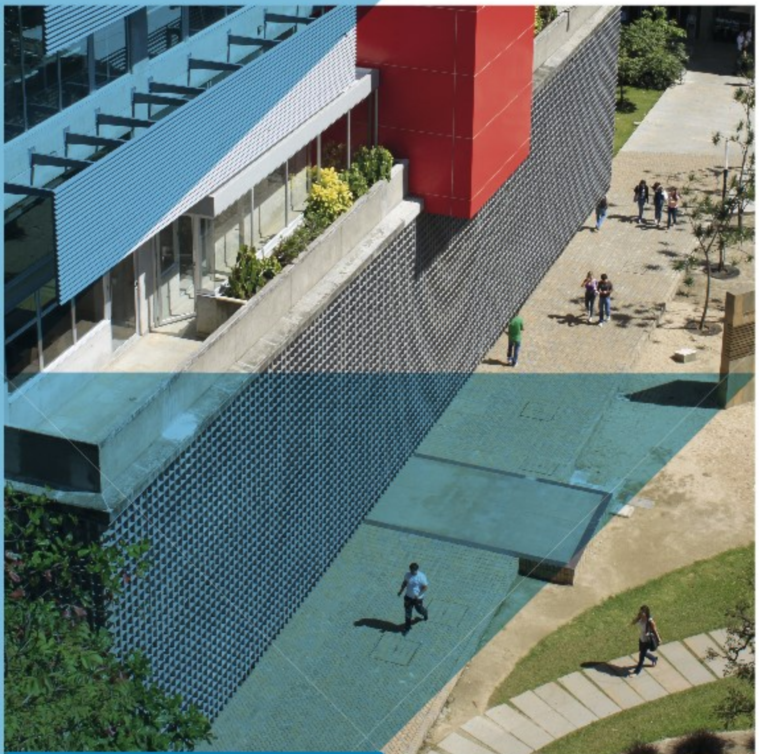

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Do news improve liquidity through improved information or visibility? Evidence from Emerging Markets.

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Do news improve liquidity through improved information or visibility?

Evidence from Emerging Markets.

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Abstract

Market microstructure models imply that informed trading reduces liquidity. We test for the effect of the frequency of new releases, as a proxy of information arrival, on liquidity in the Chilean stock market. We find that news release frequency is strongly related to improved liquidity. Those results appear for both negative a positive news days and are robust using four different measures of liquidity: bid-ask spread, Amihud measure and two versions of the Zero trading variable. We also find evidence consistent with visibility and information arrival interacting for enhancing liquidity.

JEL: G10, G15, G19

Keywords: Informed trading; liquidity; news; emerging markets; market microstructure.

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1 Introduction

Market microstructure models like Kyle (1985), Glosten and Milgrom (1985) and Easley and O'Hara (1992) postulate that informed based trading decrease liquidity, by increasing the adverse selection cost for the liquidity provider. Several empirical papers support such relation using different measures of informed trading (Easley, Engle, O'Hara and Wu 2008; Chung, Li and McInish 2005; Easley, Kiefer and O´Hara, 1997)

A variable related to information arrival, the frequency of new releases, exhibits an ambiguous relation with liquidity. At first glance, the frequency of news releases seems associated with increased information. It is expected that informed traders trade aggressively around times of increased information to exploit their information advantage (Riordan et al. 2013; Tetlock 2010). For example, informed trading activity has been detected in particular news events such as announcements of earnings (Kaniel et al. 2012) and mergers (Aktas et al. 2007; Spyrou, Tsekrekos, and Siougle 2011). Krinsky and Lee (1996) show that both bid-ask spreads and asymmetric information increases around merger announcements. On the other hand, the information incorporated in new releases should attract a larger pool of uninformed traders, that offset a possible increase in informed trading activity, as in (Blankespoor, Miller, and White 2013; Sankaraguruswamy, Shen, and Yamada 2013). Tetlock (2010) provides supportive evidence of informed trading appearing before the news, news alleviating asymmetric information, and then uninformed traders trading after the new release. In such a way, new releases tend to level the playfield. All in all, the effect of frequency of new releases on liquidity remains to be clarified.

We find that news release frequency is strongly related to improved liquidity in six emerging markets from Latin America. Those results are robust in all the six countries, and using four different measures of liquidity: bid-ask spread, Amihud measure and two versions of the Zero trading variable (Goyenko, Holden, and Trzcinka 2009). In this preliminary version of the paper we will only show the results for Chile, leaving the other five markets for future versions. Newswire frequency is measured with a unique hand collected database of number of news releases compiled by Bloomberg in a stock-day basis. To our knowledge this variable has not been used in the previous literature.

Next, we investigate the differential role of positive and negative newswires. Classical microstructure models treats all information symmetrically implying that both positive and negative informed based trading has a negative impact on liquidity. However, (Riordan et al. 2013) studying the impact of newswire messages find that negative news reduce liquidity while neutral and positive news improve it. Our evidence contradicts those results. We find that both types of news have a positive effect on liquidity. Moreover, some evidence suggests that negative news have a higher effect on liquidity. Possible explanations for this results will have to wait until a future version of this study.

Next, we test whether for interactive effects of information effect and visibility, proxied by size. Visibility enhances liquidity in the papers of Grullon, Kanatas, and Weston (2004) and Rubin and Rubin (2010) who proxy visibility by advertisement costs and Wikipedia editing frequency, respectively. Chordia, Huh, and Subrahmanyam (2006) present evidence of a positive relation between liquidity trading and visibility using company size, age, price, and book-to-market ratio as visibility proxies. We find that the positive relation between news and liquidity is even stronger for the most visible stocks. Thus, we conclude that visibility and news releases frequency interact for enhancing liquidity.

This paper contributes to two strands of the literature. On the one hand, it provides evidence in an international context of the relation between information, visibility and liquidity, so far mostly focused on US markets (Blankespoor, Miller, and White 2013; Butler, Grullon, and Weston 2005; Grullon, Kanatas, and Weston 2004; Riordan et al. 2013; Sankaraguruswamy, Shen, and Yamada 2013). On the other hand, the results contribute to a better understanding of the drivers of liquidity on emerging markets. Two direct precedents are Lesmond (2005) who studies liquidity in 31 emerging markets, and Bekaert, Harvey, and Lundblad (2007) who test whether liquidity is a priced factor in a set of 19 emerging markets, both studies using liquidity proxies

The remaining of the paper is organized as follows: Section 2 describes the data and the variables. Section 3 presents the econometric models and the corresponding results. The fourth section concludes with some suggestions for future work

2. Data and variable definition

The central variable of this paper, the news release frequency, is hand-collected from Bloomberg financial information network, using the News Trend Graph function (NT). This function provides a time-series of the number of news releases associated to a given stock, in a daily frequency. Reported news comes from more than 100 global news providers, including local agencies from emerging markets[1]. The News frequency variable (NT_{im}) is calculated summing up the news releases count in a stock-month basis. Arguably, the NT function of Bloomberg can be considered as one of the most comprehensive counts of new releases available for Emerging markets.

Closing price and quotes and volume data is collected from Datastream at daily frequency.

[1] Sources include Bloomberg News, Wall Street Journal, Financial Times, The Economist and Associated Press

The sample includes the stock exchanges of Brazil, Chile, Colombia, Mexico and Peru, for the period 1995 -2012. To avoid survivorship bias, initially we include both active and dead stocks. Foreign firms listed on those stock exchanges are also included.

Being liquidity a multidimensional concept, as widely acknowledge by the market microstructure literature, we use four different liquidity measures, the bid-ask spread, the Amihud ratio and two versions of the Zero measure (Goyenko, Holden, and Trzcinka 2009; Lesmond 2005).

The bid- ask spread is calculated from daily closing quotes, normalized by the closing middle price, and averaged in a stock-month basis as follows,

$$Bid\_ask\_spread_{im} = \frac{1}{D_m} \sum_{d=1}^{D_m} \frac{(Ask_{price_{id}} - Bid_{price_{id}})}{(Ask_{price_{id}} - Bid_{price_{id}})/2}$$

Where D_m is the number of trading days on a month.

The Amihud ratio, a proxy for price impact, is defined as follows:

$$Amihud\_ratio_{im} = \frac{1}{D_m} \sum_{d=1}^{D_m} \frac{|r_{id}|}{Volume_{id}}$$

Where r_{id} is the daily logarithmic return, and $Volume_{id}$ is the daily trading value in US dollars. To account for thin trading, we calculated daily logarithmic returns up to 3 lags. Besides, daily Amihud ratios are Winsorized at 1 and 99 percentiles as in Lesmond (2005), before being averaged in a stock-month basis.

Finally, we calculated two zero measures, defined in Goyenko, Holden, and Trzcinka (2009). $Zeros_{im}$ is the proportion of zero return days (i.e. no change in close price), on the total of trading days in a given month. In turn, $Zeros2_{im}$, calculates the proportion of days with both zero return and zero trading volume.

Summary statistics for the four liquidity measures and the new release frequency variable are listed in Table 1.

3. Econometric models and results

3.1. Effects of news release frequency on liquidity

To explore the effect of new releases on the liquidity of the Chilean stock market, we estimate the following panel data model in a stock-month basis:

$$Liquidity\,measure_{im} = \beta_{i0} + \beta_1 \log(NT_{im}) + \beta_2 volat_{im} +$$
$$\beta_3 \log(trad\_val_{im}) + \beta_3 r_{im} + \beta_4 \log(P_{im}) + \beta_4 \log(Mk\_Cap_{im}) + \mu_{it} \qquad [1]$$

Where $Liquidity\,measure_{im}$ stands for each one of the four liquidity measures described above and NT_{im} is the number of news releases. To control for any confounding factors, we include in the regression a set of control variables. Following previous cross-sectional and panel data models for liquidity measures (Chung, Elder, and Kim 2010; Grullon, Kanatas, and Weston 2004; Lesmond 2005), we include as control variables returns, r_{im}, volatility, $volat_{im}$ (standard deviation of daily log returns), price, P_{im}, market activity, measured by trading value $trad\_val_{im}$ and size, measured by market capitalization,

Mk_Cap_{im}, the last two in US dollars. To some extent size allows to control for visibility as in Chordia, Huh, and Subrahmanyam (2006) and Goyenko, Holden, and Trzcinka (2009). Model [1] includes fixed effects and is estimated using panel-corrected standard errors (PCSE) to account for heteroscedasticity, autocorrelation and cross-correlation in the residuals.

Preliminary results of model [1] are presented in Table 2. More frequent news are associated to improved liquidity, specifically, lower bid-ask spreads, and lower proportion of zero return days, and the three coefficients are significant at the 1% level. Since we are controlling for size, this positive effect seems not completely explained by visibility. Neither is explained by an increase in larger market activity, since we are controlling for trading value.

In most cases the control variables present the signs predicted by the literature (Grullon, Kanatas, and Weston 2004; Lesmond 2005). Higher trading activity, positive returns, lower volatility and higher prices are related to lower spreads, this is, improved liquidity. Notwithstanding, the results for the Zeros variables report a negative effect of volatility, which could be explained by the difficulty of measuring volatility in thinly traded stocks.

All in all, news releases seem to have a positive effect on liquidity, not explained by visibility or increased market activity. In the context of models of informed-based trading (Kyle, 1985; Easley and O'Hara, 1992; Easley, Kiefer and O'Hara, 1997) news releases can attract both informed and uninformed traders. The results are consistent with an increase in the proportion of uninformed traders after new releases, leading to increased liquidity.

3.2 Differential effects of positive and negative news releases on liquidity

Motivated by previous results by Riordan et al. (2013)we analyze if positive and negative news releases have different effects on liquidity. Since we don't observe the "tone" of individual newswires, we proxy it by the sign of the stock excess return the market index return. Arguably, in months of mostly positive (negative) news the stock excess return of tends to be positive (negative). Accordingly, we define the dummy variable $D_{pos\ im}$ to be one (zero) in months of positive excess return. In [1] we replace the news release frequency variable by its interactions with the dummy variable D_{pos}, as follows:

$$Liquidity\ measure_{im} = \beta_{i0} + \beta_1 \log(NT_{im}) \times D_{pos\ im} + \beta_2 \log(NT_{im}) \times (1 - D_{pos\ im}) + \beta_3 volat_{im} + \beta_4 \log(trad\_val_{im}) + \beta_5 r_{im} + \beta_6 \log(P_{im}) + \beta_7 \log(Mk\_Cap_{im}) + \mu_{it} \qquad [2]$$

Table 3 presents the results from model [2] in three liquidity proxies. We note that the effect of news release frequency on liquidity is positive both in positive and negative excess return months. In the lower part of Table 3 we test the statistical significance between the coefficients β_1 and β_2 on [2]. In two out of three liquidity measures the effect of positive news on liquidity is lower than the effect of negative news. Overall this results partially agree with those of Riordan et al. (2013). Whereas our results support that positive or neutral news increase liquidity, we find, contrary to them, that negative news also do it. Our results are more supportive of classical market microstructure models that treat symmetrically the two types of information. We leave this issue for future study.

3.3 Effects of news release frequency depending on size

As a robustness test we want to explore whether the results in table 2 differs on firm size. Since previous empirical studies finds a clear relation between visibility and liquidity (Chordia, Huh, and Subrahmanyam 2006; Grullon, Kanatas, and Weston 2004), by doing this we are checking for an interactive effect on liquidity coming from visibility and news release frequency. Accordingly, we classify firms by size quartiles in a yearly basis, based on the market capitalization at the end of the year. A Dummy variable D_{Q4} (D_{Q1}) is set to be one for firms in the highest (lowest) size quartile and zero, otherwise. Consequently, model [1] is modified as follows:

$$Liquidity\ measure_{im} = \beta_{i0} + \beta_1 \log(NT_{im}) + \beta_2 \log(NT_{im}) \times D_{Q1} + \beta_3 \log(NT_{im}) \times D_{Q4} + \beta_4 volat_{im} + \beta_5 \log(trad\_val_{im}) + \beta_6 r_{im} + \beta_7 \log(P_{im}) + \beta_8 \log(Mk\_Cap_{im}) + \mu_{it} \qquad [3]$$

The results of model [3] are shown in the first three columns of Table 4. The results are mixed. Whereas the negative effect of new releases frequency on the bid-ask spread seems not differ on size, a differential effect is evident in the two zero measures. The liquidity of larger firms appears to be more positively affected by the news frequency. To explore further these results, we run regression [1] for the bid-ask spread separately for each size quartile, as presented in the last four columns of Table 4. News release frequency decreases bid-ask spreads significantly only for the two top size quartiles. Taken together the results suggest that visibility, proxied here by size, reinforces the positive effect of news on liquidity.

4. Conclusions

The link between news and liquidity is still tenuous. We contribute to this literature by providing novel evidence on the positive relation between news release frequency and several liquidity variables in the Chilean stock exchange. We found that this effect is mostly concentrated in the upper half of the distribution of firms by size, which suggest an interactive effect between visibility and news frequency. Contrary to some previous literature, we provide some preliminary evidence that both positive news and negative news have such positive effect, which deserves further study.

Future work should move in the following three directions. First, we will gather evidence on the other 5 stock exchanges of Latin America. It is important to verify if the preliminary findings are sustained in a larger sample. Second, we will further explore the differential effects of positive and negative news on liquidity, which might require a better measure the tone of the news. Finally, we will explore the connection between news and information. News is not necessarily information, if the content of the news were known facts for informed traders. On the contrary, the positive effect on liquidity can be explained as news releases simply attracting attention of uninformed traders. A deeper understanding of that connection requires a measure of informed trading, for example the dynamic PIN measure ((Easley et al. 2007), which has been estimated for Latin American markets by (Villarraga, Giraldo, and Agudelo 2012)

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Table 1. Summary statistics for the liquidity measures and News release frequency.

Variable	P 5	P 50	P 95	Obs	Mean	Std. Dev.
$Amihud\_ratio_{im}$	0,00000	0,00033	0,01158	29242	0,00285	0,01351
$Bid\_ask\_spread_{im}$	0,47%	3,99%	38,46%	11830	9,24%	12,98%
$Zeros_{im}$	5%	100%	100%	68040	80%	31%
$Zeros2_{im}$	0,0%	0,0%	36,4%	68040	8,7%	13,3%
NT_{im}	0,0	0,0	9,0	60264	2,0	11,4

Table 2 The effect of news release frequency on liquidity measures

Dependent variable	$\log(Bid\_ask\_spread_{im})$	$Zeros_{im}$	$Zeros2_{im}$
$\log(NT_{im})$	-0.0011***	-0.0049***	-0.0114***
	(0.0002)	(0.0012)	(0.001)
$volat_{im}$	0.0209***	-0.0415***	-0.0371***
	(0.0012)	(0.0017)	(0.0018)
$\log(trad\_val_{im})$	-0.0016***	-0.0505***	-0.0018**
	(0.0002)	(0.0007)	(0.0006)
r_{im}	-0.0190***	-0.0687***	0,0045
	(0.0021)	(0.0052)	(0.0049)
$\log(P_{im})$	0,0027	-0.0113**	-0.0267***
	(0.0019)	(0.0041)	(0.0033)
$\log(Mk\_Cap_{im})$	-0.0067***	-0.0181***	-0.0157***
	(0.0011)	(0.0016)	(0.0013)
N	8167	24380	24380
df	179	232	232
chi2	3701	83072	10802
P-value	0,000	0,000	0,000

*, **, ***: Significantly different from zero at the 10%, 5% and 1% respectively. Standar errors, adjusted for heteroscedasticity and autocorrelation, reported below in parenthesis.

Table 3. The differential effect of positive and negative news release frequency on liquidity measures

Dependent variable	$\log(Bid\_ask\_spread_{im})$	$Zeros_{im}$	$Zeros2_{im}$
$\log(NT_{im}) \times D_{pos\ im}$	-0.0008***	-0.0039**	-0.0117***
	(0,0002)	(0,0013)	(0,0011)
$\log(NT_{im}) \times (1 - D_{pos\ im})$	-0.0014***	-0.0058***	-0.0110***
	(0,0003)	(0,0013)	(0,0011)
$volat_{im}$	0.0208***	-0.0417***	-0.0370***
	(0,0012)	(0,0017)	(0,0018)
$\log(trad\_val_{im})$	-0.0015***	-0.0505***	-0.0018**
	(0,0002)	(0,0007)	(0,0006)
r_{im}	-0.0218***	-0.0713***	0,006
	(0,0023)	(0,0054)	(0,0051)
$\log(P_{im})$	0,0028	-0.0115**	-0.0267***
	(0,0019)	(0,0041)	(0,0033)
$\log(Mk\_Cap_{im})$	-0.0067***	-0.0180***	-0.0158***
	(0,0011)	(0,0016)	(0,0013)
N	8167	24380	24380
df	180	233	233
chi2	3735	82992	10825
P-value	0,000	0,000	0,000
Pos-neg	0.00056***	0.0019*	-0,00075
Estadístico t: Pos-Neg=0			
P-value	0,005	0,059	0,369

*, **, ***: Significantly different from zero at the 10%, 5% and 1% respectively. Standar errors, adjusted for heteroscedasticity and autocorrelation, reported below in parenthesis.

Table 4. The effects of news release frequency on liquidity measures depending on size.

Dependent variable	$\log(Bid\_ask\_spread_{im})$	$Zeros_{im}$	$Zeros2_{im}$	$\log(Bid\_ask\_spread_{im})$ Quartile1	Quartile 2	Quartile 3	Quartile 4
$\log(NT_{im})$	-0.0019***	-0,0011	-0.0077***	0,0018	-0,0016	-0.0016**	-0.0008***
	(0,0005)	(0,0023)	(0,0019)	(0,0056)	(0,0017)	(0,0006)	(0,0002)
$\log(NT_{im}) \times D_{Q4}$	0,0009	-0.0051*	-0.0056**				
	(0,0006)	(0,0026)	(0,0021)				
$\log(NT_{im}) \times D_{Q1}$	0	0,0025	0.0148*				
	(0,0046)	(0,0074)	(0,0075)				
$volat_{im}$	0.0210***	-0.0417***	-0.0372***	0.0190***	0.0147***	0.0215***	0.0194***
	(0,0012)	(0,0017)	(0,0018)	(0,0048)	(0,0022)	(0,0022)	(0,0015)
$\log(trad\_val_{im})$	-0.0015***	-0.0506***	-0.0018**	-0.0065*	-0.0065***	-0.0017***	-0.0011***
	(0,0002)	(0,0007)	(0,0006)	(0,0026)	(0,0009)	(0,0004)	(0,0002)
r_{im}	-0.0193***	-0.0691***	0,0041	-0,0364	-0.0262***	-0.0192***	-0.0148***
	(0,0021)	(0,0052)	(0,0049)	(0,023)	(0,006)	(0,004)	(0,0021)
$\log(P_{im})$	0,0026	-0.0106**	-0.0261***	-0,063	0,0107	-0,0034	0,004
	(0,0019)	(0,0041)	(0,0033)	(0,0434)	(0,0138)	(0,0062)	(0,0023)
$\log(Mk\_Cap_{im})$	-0.0068***	-0.0178***	-0.0153***	0,0041	0,0024	-0,0027	-0.0085***
	(0,0011)	(0,0016)	(0,0013)	(0,0149)	(0,0049)	(0,0025)	(0,0016)
N	8167	24380	24380	277	1261	2305	4318
df	181	234	234	24	60	91	87
chi2	3720,7357	82695,579	10521,115	248,0622	2124,4345	1489,2654	1505,806

*, **, ***: Significantly different from zero at the 10%, 5% and 1% respectively. Standard errors, adjusted for heteroscedasticity and autocorrelation, reported below in parenthesis.