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Full Length Research Paper

Verifying the presence of the liquidity premium in the Brazilian market through different time scales

Marcelo Brutti Righi* and Kelmara Mendes Vieira

Universidade Federal de Santa Maria, Avenida Roraima, 1000, Santa Maria, Brazil.

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In this paper, we propose a new approach, wavelet analysis for investigating the relationship between liquidity and stock returns in the Brazilian market over different time scales. To that we used daily quotations of the Ibovespa from January, 2002 to April, 2010, totalizing 2049 observations. As proxy of liquidity, we used the measure proposed by Amihud (2002). The descriptive results appointed for a solidification of the Brazilian market in terms of financial volume, beyond the stabilization in the general liquidity. Further, we verified the existence of a liquidity premium considering the distinct negotiation frequency scales. The results confirmed some previous studies, indicating that in the Brazilian market, keep illiquidity assets in a portfolio has a cost in the form of an extra return. Nonetheless, the finest scales exhibited higher values for the parameters of the illiquidity in the regressions. This fact is associated with the need of the short-time investors, which correspond to the speculative capital, than that of the long-term conservator ones.

Key words: Brazilian market, liquidity risk, wavelets, scales.

INTRODUCTION

The stock market plays a vital role in the modern economy since it acts as a mediator between lenders and borrowers. That is, a well-functioning stock market may assist the development process in an economy through two important channels: boosting savings and allowing for a more efficient allocation of resources.

Investors have a great interest in discovering variables that may help forecast stock prices. They can more appropriately manage their positions and portfolios (increase returns and/or lower risk) if they can use market news releases as reliable indicators for where the stock market is headed.

Therefore, a variable that plays an important role in this purpose is the liquidity. Accordingly to Amihud and Mendelson (2006), an asset is considered liquid if it could be quickly negotiated at the market value and at a low cost. Illiquid assets require higher transaction costs when negotiated. Thus, these assets should offer a liquidity prize because investors require to be compensated for trading in illiquid stocks. Based on this perspective, any investor is exposed to the liquidity risk. Thus, liquidity should be considered in investment decisions. So many researches have been developed to determine the relationship between liquidity and return in financial markets (Hameed et al., 2010). However, there is no consensus about the found results. This controversy is caused by the fact that distinct methodologies, samples and periods were used, making hard any kind of comparison.

Although most of the researches were performed in the United States market (Amihud and Mendelson, 1986, 1989; Datar et al., 1998; Liu, 2006), the influence of the liquidity in the pricing of financial assets have been studied in several countries (Jun et al., 2003). The choice for other markets, especially emerging countries, is justified due to the heterogeneity in the liquidity inherent to these markets.

In that sense, the main objective of this paper is to propose a new approach, wavelet analysis, for investigating the relationship between liquidity and stock returns in the Brazilian market over different time scales.

*Corresponding author. E-mail: marcelobrutti@hotmail.com. Tel: +555591948664.

To that we used daily quotations of the Ibovespa from January, 2002 to April, 2010, totalizing 2049 observations. As proxy of liquidity we used the measure proposed by Amihud (2002).

The current approach is based on a wavelet multiscaling method that decomposes a given time series on a scale-by-scale basis. Accordingly to Gençay et al. (2003), the main advantage of wavelet analysis is the ability to decompose the data into several time scales and ability to handle nonstationary data, localization in time, and the resolution of the signal in terms of the time scale of analysis.

Since it is likely that there are the different decision-making time scales among traders, the true dynamic structure of the relationship between liquidity and stock returns will vary over different time scales associated with those different horizons. Wavelet analysis extends previous investigations that were only compared with the short run and the long run.

The sequence of this paper is structured on the following way: materials and methods of the study, explanation of the data and the procedures to achieve the objective of the paper; results and discussion; conclusions.

MATERIALS AND METHODS

Two aspects will be considered here: i) wavelets, which briefly explains about the principal quantitative technique applied in this paper; and ii) empirical method, which expose the used procedures in order to achieve the proposed objective.

Wavelets

Wavelets, as is suggested by their name, are little waves. The term wavelet was created in the geophysics literature by Morlet et al. (1982). However, the evolution of wavelets occurred over a significant time scale and in many disciplines, and their background can be finding in Daubechies (1992), Meyer (1993), Vidakovic (1999), Heil and Walnut (2006), among others.

Basic wavelets are characterized into father and mother wavelets. A father wavelet (scaling function) represents the smooth baseline trend, while mother wavelets (wavelet function) are used to describe all deviations from trends (Kim and In, 2005). Father and mother wavelets are represented by formulations 1 and 2, respectively:

$$\phi_{j,k}(x) = 2^{j/2}\phi(2^j x - k). \tag{1}$$

$$\psi_{j,k}(x) = 2^{j/2}\psi(2^j x - k). \tag{2}$$

Where, $j, k \in \mathbb{Z}$, for some coarse scale j_0, that will be taken as zero. From these expressions an orthonormal system is generated. Conform (Morettin et al., 2010), for any function f that belongs to this system we may write, uniquely:

$$f(x) = \sum_k \alpha_{0,k}\, \phi_{0,k}(x) + \sum_{j\geq 0}\sum_k \beta_{j,k}\psi_{j,k}(x) \tag{3}$$

In formulation 3, $\alpha_{0,k} = \int f(x)\,\phi_{0,k}\,dx$ and $\beta_{j,k} = \int f(x)\,\psi_{j,k}\,dx$ are the wavelet coefficients. Thus, consider a time series, *f(t)*, which we want to decompose into various wavelet scales. Given the father wavelet, such that its dilates and translates constitute orthonormal bases for all the subspaces that are scaled versions of the initial subspace, we can form a Multi resolution analysis (MRA) for *f(t)* (Burrus et al., 1998).

In economics and finance wavelet analysis has previously been applied to the examination of foreign exchange data using waveform dictionaries (Ramsey and Zhang, 1997), decomposition of economic relationships of expenditure and income (Ramsey and Lampart, 1998), systematic risk in a capital asset pricing model (Gençay et al., 2003), beyond the paper of Ramsey (2002) and the book by Gençay et al. (2002).

Empirical method

In order to investigate the relationship between liquidity and stock returns in the Brazilian market over different time scales, we used daily quotations and volume of Ibovespa from January, 2002 to April, 2010, totalizing 2049 observations. This index is commonly used in academic papers as proxy for this financial market. Daily data provides more observations, a fundamental feature in the analysis of distinct time scales. After, we calculated the log-returns of market, conform formulation 4:

$$r_t = (\ln P_t - \ln P_{t-1}) \times 100. \tag{4}$$

In formulation 4, P_t is the daily quotation in period *t* of the Ibovespa, whereas r_t represents its log-return at time *t*. Thus we have 2048=2^{11} observations of each variable. This is necessary because wavelets decomposition works with number of data in form of power of two. We choose not to use data previous of 1995 because it was a period with huge inflation, which could cause some biases.

The liquidity measure adopted in this study was adapted from that proposed by Amihud (2002). This measure, represented by formulation 5, actually identifies the Illiquidity of determined asset:

$$I_t = \ln\left(\frac{r_t}{V_t}\right). \tag{5}$$

In 5, I_t is the illiquidity of Ibovespa in period *t*; r_t represents its log-return at time *t*; V_t is the financial volume of the Brazilian market in the day *t*. The daily volumes were divided by 10^9 to be in the same magnitude of the log-returns.

After we realized the MRA, proposed in materials and methods, for both variables. Thus we obtained eleven groups of coefficients ($2^0 + 2^1 + \cdots + 2^{10} = 2048$), which represents the distinct frequency levels of each discrete decomposition. This step was based in the Haar mother wavelet, which is represented by formulation 6:

$$\psi(x) = \begin{cases} 1, x \in [0\,,1/2) \\ -1, x \in [1/2,1) \\ 0 \; otherwise \end{cases}. \tag{6}$$

In that sense, Nason (2008) appoints that the Haar wavelet is a good choice because it exhibits many characteristic features of wavelets. Two relevant characteristics are the oscillation (the Haar wavelet goes up and down), mathematically this can be expressed by the condition that $\int_{-\infty}^{\infty} \psi(x)dx = 0$, a property shared by all wavelets; and the compact support (not all wavelets have compact support, but they must decay to zero rapidly).

Subsequently, through this discrete decomposition, we formed pairs composed by the 0 to 11 levels of log-returns decomposed from both variables. With each pair *i*, we estimated an equation, with the form (7), to verify the impact of the illiquidity in the return:

$$r_{t,i} = \alpha_i + \beta_i I_{t,i} + \varepsilon_{t,i}. \qquad (7)$$

In 7, α_i and β_i are the regression coefficients estimated by maximum-likelihood; $\varepsilon_{t,i}$ is the residual term; Due to the low number of coefficients in the very first four levels (0 to 3 scales), we just calculated its linear correlations, to avoid any problem with a possible over fitting. In order to perform a comparison of the current approach with those traditional ones (Fama and French, 1992, 1993), we estimated a model similar to (7) considering the whole sample, without distinction of time scales.

RESULTS AND DISCUSSION

Initially, we made a descriptive analysis of the utilized data. Figure 1 presents the temporal evolution of the daily volumes, prices, log-returns and illiquidity variation of the Brazilian market during the studied period. The plots in Figure 1 reveal some interesting information. First, there was a growth in the Brazilian market volume during the last decade years, leveraged by the consolidation of the economy of the country.

Further, it is possible to percept effects of the 2007/2008 sub-prime crisis. There were huge falls in the daily volumes and prices around observations 1550 to 1950, representing the two years of turbulence. This turbulence is registered by the volatility cluster of the log-returns, during the same period. Regarding to illiquidity, one can note that there was great oscillation in beginning of the series, reaching stabilization with the long of the sample. This fact corroborate with the economic consolidation of the Brazilian market, which became a concise option for international investors.

Continuing with this initial analysis, are presented in Table 1 the descriptive statistics of the daily returns of the Ibovespa and its illiquidity. The results contained in Table 1 indicate that both the series have related characteristics, as very close to zero mean and similar dispersion. However, regarding the skewness and kurtosis, despite both series be negative asymmetric and leptokurtic, the illiquidity obtained bigger magnitudes for these measures. This result can be explained due to that initial period of high turbulence in the illiquidity, raising the quantity of values away from the central tendency, as well the abrupt reductions of the volume during the turbulence periods.

Subsequently to this initial descriptive analysis, we realized the MRA, proposed in materials and methods, for both variables. Figure 2 illustrates the obtained coefficients in the 11 levels (2048 = 2^{11} observations). Figure 2 emphasizes that at finest scales, there were much more oscillation in both series due to the intense activity existing in the whole financial market at the short-term. Further, the variations in the Brazilian stock market were bigger during the sub-prime crisis period, while the turbulence in the illiquidity predominated in the beginning of the sample, when the Brazilian market was not a stable one. This result corroborates with those found in the previous descriptive analysis.

Complementing, Figure 3 presents the calculated correlation between the variables for each resolution scale. With exception of the scale 2, the finest scales presented lower correlations than the coarse ones. However, the magnitude of this dependence was never smaller than 65%, expressing a tight relation between the illiquidity and the return. This result highlights the importance of researches in this field in emerging markets. In these countries still there is no homogeneity in the liquidity of stocks, making inherent the presence of premiums in the form of compensation for the illiquidity risk.

After, we tested the presence of a liquidity premium in the Brazilian market, considering distinct frequencies, through the regressions presented in 7. We also estimated a regression model for the whole sample in order to compare the proposed approach with the traditional ones. The results of the estimated regression for the traditional approach serve as a benchmark of the sensibility of the returns in the Brazilian stock market in relation to the oscillations in its illiquidity level. The results of this step are exposing in Table 2.

The results in Table 2 initially exhibit that the illiquidity significantly affects the returns of the Brazilian stock markets in all the estimated regressions. This is evidence that there is a liquidity premium in the Brazilian market, independently of the resolution scale in which the negotiations were realized. These findings corroborate with some previous studies which attest for the existence of the liquidity premium in the Brazilian stock market.

The financial interpretation of the estimated parameters for the illiquidity in the regression model is as follows: for each unit variation in the illiquidity, there is an expected oscillation of magnitude β in the returns of the Brazilian stock market in determined time scale. This value is the average liquidity premium sensibility of the market in that time scale. For example, for scale 7, a unit variation in the illiquidity causes an expected oscillation around 0.53 in the general return of the market in that frequency.

Despite the findings for the linear correlation, it is possible to observe that the bigger values for the sensibility (β parameter) to the illiquidity oscillations are in general for the finest scales. Although, the greater value for this parameter was obtained at the scale 6, a relatively median frequency. This result emphasizes that the short-term investors are more sensible to oscillations in the market liquidity than those ones, which prefer long-term positions, seeking a gradual evolution of the stocks that compose their portfolios. Figure 4 graphically

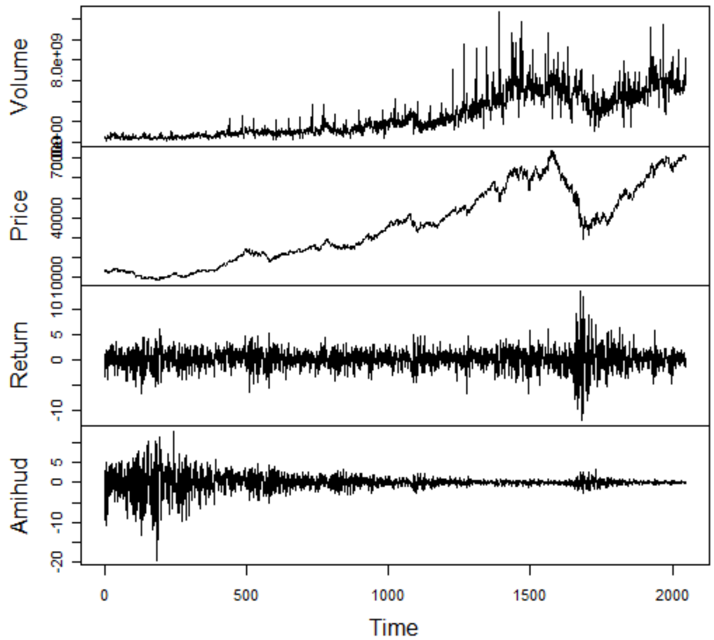


Figure 1. Temporal evolution of the daily volumes, prices, log-returns and illiquidity variation of the Brazilian market.

Table 1. Descriptive statistics of the daily returns and illiquidity of the Brazilian market.

Statistic	Returns	Illiquidity
Minimum	-12.0961	-19.4333
Maximum	13.6794	12.9279
Mean	0.0795	0.0177
Standard deviation	1.9926	2.0855
Skewness	-0.1023	-0.9578
Kurtosis	4.3139	11.6335

presents the coefficients of the illiquidity obtained in each regression.

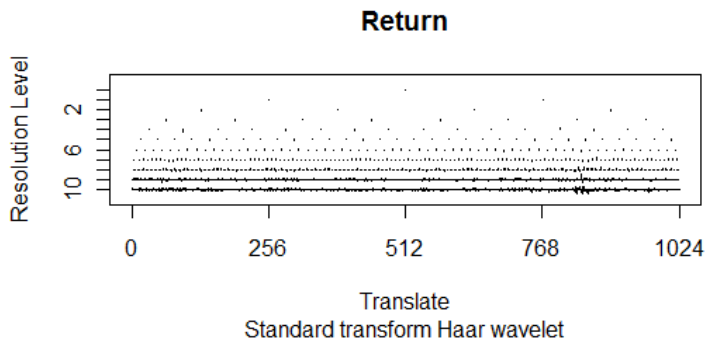
Further, all the regressions were significant, as indicated by the *F* tests, with explication degrees at order to 44 to 56%, frizzing the importance of the factor liquidity in the pricing of financial assets. In comparison with the traditional approach, one can note that the magnitude of the β parameter of the regression for the whole sample was very close to those estimated in the equations of the finest scales. This is normal because the last scales in the MRA tend to the daily frequency, which is captured in the "raw" data. It is valid to note that the degree of explanation of the traditional regression was equated overcame by practically all the scaled equations, revealing the need for a proper distinction of the trading frequency in the studied market.

Again, these results reinforce the heterogeneity of the Brazilian (and emerging in general) markets. Beyond the huge discrepancy among distinct kinds of stocks, there is, still, a considerable difference in the liquidity preference regarding to the style of the investors. Clearly there is a bigger need of the short-time investors, which correspond to the speculative capital for liquidity, than that of the long-term conservator ones.

Conclusions

In this paper we aimed to investigate the relationship between liquidity and stock returns in the Brazilian market over different time scales. To that, we use daily data from Ibovespa. As proxy for the liquidity (illiquidity), we employed the measure proposed for Amihud (2002). The wavelets MRA was used for discretely obtain the set of parameter for each frequency scale.

The first descriptive results appointed for a recent



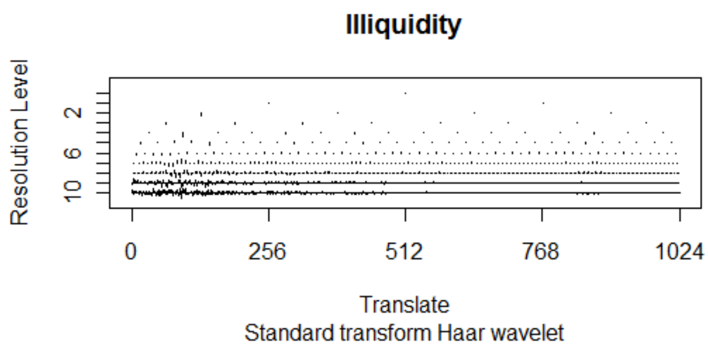


Figure 2. Coefficients of the MRA for 11 scales of daily returns and illiquidity of the Brazilian market.

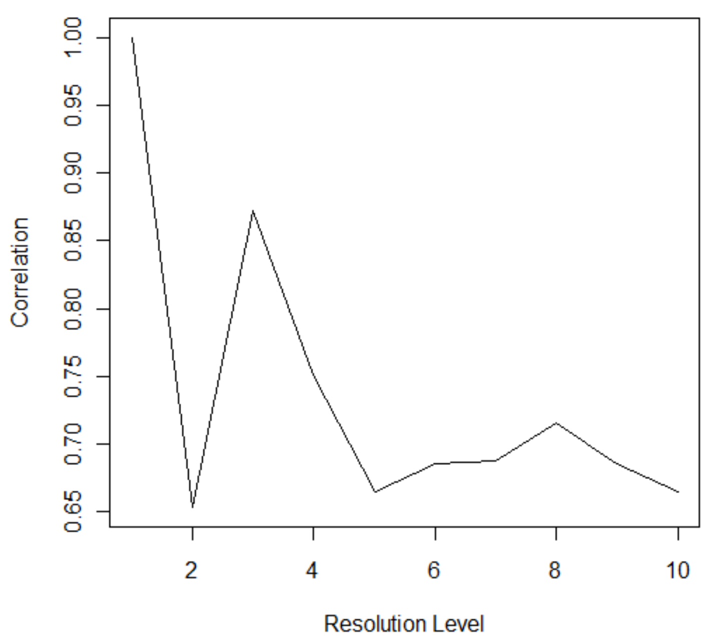


Figure 3. Correlation between returns and illiquidity in the Brazilian market in the different frequency scales.

solidification of the Brazilian market in terms of financial volume, beyond the stabilization of the oscillations in the general liquidity. Further, we found some vestiges of the sub-prime crisis of 2007/2008 in the log-returns of the

Table 2. Results for the estimated regressions of the return in the illiquidity in the Brazilian market in distinct scales (wavelet analysis) and in the whole sample (traditional approach).

Scale	*α*	*β*	R^2	*F*-test
4	0.2094	0.5363	0.5640	18.1100
	(0.5969)	(0.0008)	-	(0.0008)
5	0.2545	0.5081	0.4422	23.7800
	(0.2250)	(0.0000)	-	(0.0000)
6	0.0833	0.7341	0.4696	54.8800
	(0.6336)	(0.0000)	-	(0.0000)
7	0.0739	0.5363	0.4730	113.1000
	(0.5030)	(0.0000)	-	(0.0000)
8	0.1006	0.6632	0.5128	267.3000
	(0.2430)	(0.0000)	-	(0.0000)
9	0.0320	0.6359	0.4708	453.8000
	(0.6210)	(0.0000)	-	(0.0000)
10	-0.1275	0.6734	0.4424	810.9000
	(0.0077)	(0.0000)	-	(0.0000)
Whole	0.0680	0.6478	0.4594	1740.6340
	(0.0359)	(0.0000)	-	(0.0000)

*Bold values are significant at 1% level.

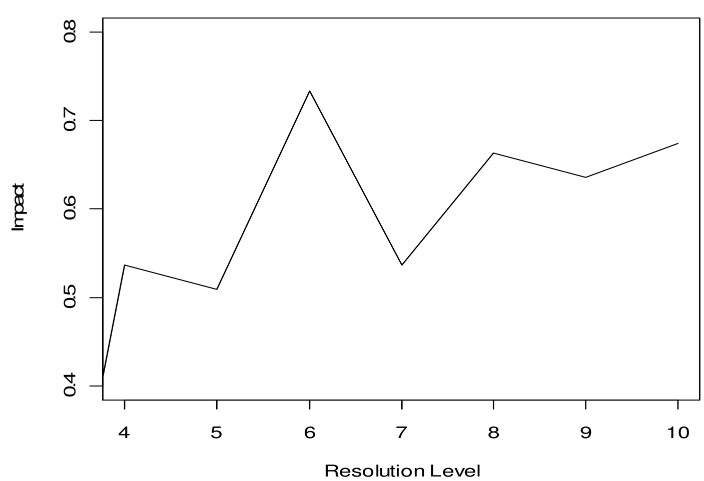


Figure 4. Estimated coefficients of the illiquidity at the regression of the returns of the Brazilian market for each frequency scale.

market. After, based on the realized MRA, we verify the existence of a liquidity premium considering the distinct negotiation frequency scales. The results confirmed some previous studies, indicating that in the Brazilian market, keep illiquidity assets in a portfolio has a cost in the form of an extra return.

Nonetheless, there was a considerable difference in the magnitude of the sensibility of the returns in relation to the illiquidity in the distinct scales. In general, the finest scales exhibited higher values for the parameters of the illiquidity in the regressions, reinforcing the characteristic heterogeneity of the studied market. This fact is associated with the need of the short-time investors, which correspond to the speculative capital for liquidity, than that of the long-term conservator ones. The short-time investors seek for quickly diversification of their portfolios, beyond facility to pay off the positions and leave a specific market.

It is valid to note that the degree of explanation of the proposed approach was superior to that obtained with the traditional, revealing the need for a proper distinction of the trading frequency in the studied market. Regarding to practical matters, an investor should take in count the estimated liquidity premium for his/her trading frequency scale in order to appropriately determine the risk of determined market or specific asset. The omission or wrong estimation of this premium can lead to suboptimal capital allocations due to the imprecise risk determination of the traded asset.

Finally, we suggest for future studies that similar approach be utilized in researches of liquidity premium in other emerging markets, in order to consolidate the existence of a sizeable heterogeneity in the liquidity of the stock markets in these countries.

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