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Decomposing the bid-ask spread in the Brazilian market: an intraday framework

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Abstract

In this paper, we identify the bid-ask spread components in the Brazilian market at intraday high frequency. To do so, we use data from all stocks that compose the Ibovespa in 10-minute frequencies from January to March of 2013. We use the model of Huang and Stoll (1997). Preliminary results indicate that there is a relatively stable pattern in the temporal evolution of the means of the bid-ask spread percentage with a distinct seasonal effect linked to the opening and closing of the Brazilian market. Regarding the proportion of components, adverse selection costs exhibit the lowest participation in the bid-ask spread of stocks in the Brazilian market (approximately 3%); inventory holding costs have the largest participation (approximately 52%), followed by the order processing costs component (45%). The presented results highlight the importance of liquidity over information asymmetry as the observed pattern diverges from those obtained in previous studies conducted in developed markets.

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1. Introduction

The central feature of capital market operations is the ability to buy or sell large quantities of assets quickly and at a low cost. This feature is known as market liquidity. In recent years, an increase in interest regarding financial market liquidity and its relation to asset prices has been observed. Since the seminal work of Amihud and Mendelson (1986), empirical literature has recognized that asset illiquidity has significant impact on securities pricing. Accordingly, some works have documented the role of liquidity as a determinant of expected returns (Amihud, 2002; Liu, 2006; Hwang and Lu, 2009), while others emphasize liquidity risk, which is basically the possibility of a loss of asset value due to low liquidity, of expected stock returns (Pástor and Stambaugh, 2003; Acharya and Pedersen, 2005; Lin et al., 2011).

The difference between the price at which a liquidity supplier is willing to buy an asset and that at which he is willing to sell, the bid-ask spread, is the subject of much interest among financial market participants and securities regulators. The size of the spread measures market liquidity and ultimately determines whether the liquidity supplier is successful. Existing market microstructure models incorporate, at most, three cost factors that market makers consider when setting the spread for a specific stock. These factors include their order processing costs (Stoll, 1978), their inventory holding costs for the stock (Ho and Stoll, 1981), and the costs arising from trading against a better-informed counter party (Glosten and Milgrom, 1985).

More specifically, the order processing cost component represents the fee charged by market makers so they can be prepared to match buying and selling orders. The adverse selection component is the cost of market makers taking the risk of dealing with traders who may possess superior information, and the inventory holding component is the compensation for a dealer holding a less diversified portfolio. In addition to these factors, market watchers expect that market-wide trends might be a factor in setting the spread.

Thus, it is crucial to establish models for the correct decomposition of the spread because financial agents require detailed information when making decisions. For example, the bid-ask spread for assets *A* and *B* can be equal, but for *A*, the spread is due to lack of liquidity, while for *B*, the spread is related to asymmetry in information. Such knowledge can be used in asset pricing or for risk management purposes, for instance.

Spread decomposition models rely on the assumption that the uncertainties in order flow can result in inventory problems for market makers. As order flow does not always balance due to unpredictable supply and demand, market makers often carry inventory in the course of supplying liquidity and, hence, bear risk. Corroborating the existence of common components to short-horizon returns, order flow and liquidity have recently received a substantial amount of attention in the literature. Studies by Chordia et al. (2000), Hasbrouck and Seppi (2001) and Huberman and Halka (2001) focus on common determinants of liquidity and provide evidence that stock liquidity proxies, including bid-ask spreads, exhibit common variation over time.

Hence, the development of spread decomposition models has offered a straightforward way to decompose the spread, thus enabling adverse selection costs to be measured empirically. However, the weakness of these models is that they have yielded varied estimates with respect to component costs. Models by Glosten and Harris (1988) find that adverse selection costs are approximately 35% of the spread, while those of Huang and Stoll (1997), Madhavan, et al. (1997) and George et al. (1991) estimate the costs to be 21%, 43% and less than 10% of the spread, respectively.

Moreover, studies that have examined whether the magnitude of information asymmetry in financial markets varied in response to regulatory or institutional developments have obtained conflicting results depending on the precise spread decomposition model used (see Chiyachantana, et al. (2004) or Jiang and Kim (2005), for instance). Neal and Wheatley

(1998) and Van Ness et al. (2001), among others, also raise concern about the effectiveness of spread decomposition models.

Despite this criticism, however, the spread decomposition models are a relevant tool for obtaining information for investors, as previously noted. Further, the majority of studies regarding bid-ask spread decomposition are conducted using developed markets. Thus, the choice for other markets, such as those in emerging countries, is justified due to the heterogeneity in the liquidity inherent to these markets. Accordingly, we apply the most relevant spread decomposition model to the Brazilian equity market while considering individual stocks. Moreover, we focus on the intraday frequency as spread dynamics are more explicit.

The estimation of spread components have important implications for market microstructure research, as noted, for example, by Easley et al. (2002), who found that the probability of information-based trading significantly affects the required rate of return for a stock. Empirically, transactions are irregularly spaced in time as some of them occur minutes or seconds further apart than others. In addition, agreed upon prices are discrete and change in multiples of the smallest allowed price unit. Most notably, during a one day period, volatility and trading volume patterns have been documented. Recent empirical research strongly suggests that high frequency data exhibit strong dependencies not found in daily, weekly or monthly data.

Thus, our main objective, as well as our contribution to the literature, is the identification of the bid-ask spread components in the Brazilian market at intraday high frequency. By fulfilling this goal, it is possible to retrieve information for investors in this market, and thus, to understand how the spread components are linked. Moreover, such patterns in decomposition structures best elucidate the current liquidity problem in the Brazilian market

The remainder of this paper is structured as follows. Section 2 presents the main bid-ask spread decomposition models used in the empirical finance literature; section 3 exposes the data and methodological procedures used in the study; section 4 presents and discusses the results; section 5 summarizes and concludes the paper.

2. Bid-ask spread decomposition models: a brief review

In this section, we briefly present, in chronological order, the most relevant bid-ask spread decomposition models. We limit our focus to the studies that propose models that obtained the greatest success according to the financial literature. To have a leaner section, we avoid citing empirical works that consist of applications of the models.

2.1 The Glosten and Harris (1988) model

The first attempt at decomposing the spread is that of Glosten and Harris (1988), who based their model on the following representation of intrinsic and observed transaction prices. Under this framework, we have the following system of equations:

$$P_t = M_t + C_t Q_t, \tag{1a}$$
$$M_t = M_{t-1} + Q_t Z_t + U_t, \tag{1b}$$
$$C_t = c_0 + c_1 V_t, \tag{1c}$$
$$Z_t = z_0 + z_1 V_t. \tag{1d}$$

where P_t is the observed transaction price, M_t is the intrinsic value of the security and V_t is the number of shares in the transaction at time t. U_t captures the arrival of public information and any rounding error. Q_t is a trade indicator that is represented by +1 if the transaction is buyer initiated and -1 if the transaction is seller initiated. The adverse selection component is Z_t, and the order processing component is C_t; both are linear functions of V_t. Solving for the price change and incorporating the equations for Z_t and C_t results in equation (2).

$$\Delta P_t = c_0 \Delta Q_t + c_1 \Delta(Q_t V_t) + z_0 Q_t + z_1 Q_t V_t + U_t. \tag{2}$$

Thus, the bid-ask spread is measured as the sum of the order processing and adverse selection components, $2(c_0+c_1V_t)$ and $2(z_0+z_1V_t)$, respectively.

2.2 The Stoll (1989) model

Unlike most other models, the Stoll (1989) model, which is based on the serial covariance of quoted prices (bid or ask) and transaction prices, identifies all three cost components of spreads in three steps. First, the constants (a_0 and b_0) and the slope coefficients (a_1 and b_1) are estimated as:

$$cov_T = a_0 + a_1 S^2 + \mu, \tag{3a}$$
$$cov_Q = b_0 + b_1 S^2 + \nu. \tag{3b}$$

where S is the quoted proportional spread, cov_T is the covariance of transaction price changes, cov_Q is the serial covariance changes in ask (or bid) quotes, μ and ν are random error terms.

Second, it is necessary to estimate π, the probability of reversal in transaction, and δ, the size of the continuation in price as a fraction of the spread. These parameters are calculated from Equations (4a) and (4b) with the use of a_1 and b_1 estimated in the previous step.

$$a_1 = \delta^2(1-2\pi) + \pi^2(1-2\delta), \tag{4a}$$
$$b_1 = \delta^2(1-2\pi). \tag{4b}$$

Under this model, the accomplished spread is given by $2(\pi-\delta)S$, which is the expected profit per trade (as a percentage of stock price), and covers only the order processing and inventory holding cost components. Finally, the cost components of the quoted bid-ask spreads could be estimated as $1-2\delta$ for the order processing costs, $2(\pi-0.5)$ for the inventory holding costs, and $1-2(\pi-\delta)$ for the asymmetric information costs.

2.3 The George, et al. (1991) model

An important innovation of the model developed by George, et al. (1991) is its ability to account for serial correlation introduced by time variation in expected returns. Their model assumes that time variation influences both transaction prices and quotes, as represented herein. In this model, logarithmic prices P_t evolve the log of the midpoint M_t plus the spread component $\pi(S_q/2)Q_t$, with Q_t as +1/-1 the trade indicator variable and S_q as the percentage bid-ask spread. The fraction of the spread due to order processing costs is π, and the fraction due to adverse selection costs is $(1-\pi)$. E_t is the expected return between time $t-1$ and time t and U_t, captures the arrival of public information innovations. As there is an important timing distinction between transactions and quotes, the T subscript refers to the timing of quote information and t refers to the timing of transactions. Thus, the models are also a system of equations and conform to:

$$P_t = M_t + \pi(S_q/2)Q_t, \tag{5a}$$
$$M_t = M_{t-1} + E_t + (1-\pi)\left(\frac{S_q}{2}\right)Q_t + U_t, \tag{5b}$$
$$P_T = M_T, \tag{5c}$$
$$M_T = M_{T-1} + E_T + (1-\pi)\left(\frac{S_q}{2}\right)Q_T + U_T. \tag{5d}$$

After solving for the transaction return in time *t*, solving for the midpoint return in time *T-1* to time *T*, and subtracting the midpoint return from the transaction return, we obtain formulation (6), which can be estimated.

$$\Delta P_t = a + (b/2)(Q_t - Q_{t-1})S_q + V_t. \tag{6}$$

where V_t is an error term equal to $(E_t - E_T) + (U_t - U_T)$.

2.4 The Lin et al. (1995) model

The transaction process in the model proposed by Lin et al. (1995) incorporates the superior information of the informed trader in a transaction at time t. The revelation of information at the time of the trade then leads to a quote revision following the trade. When quote revisions are not undertaken swiftly enough by market makers, a possible information asymmetry between market makers and informed traders arises and is reflected in the half spread. In this model, the quote and transaction process is expressed by:

$$M_t - M_{t-1} = \lambda z_{t-1} + \varepsilon_t, \tag{7a}$$
$$z_t = \theta z_{t-1} + \eta_t. \tag{7b}$$

where M_t is the quote mid-point at *t*, $z_t = P_t - M_t$ and is the signed half effective spread (if a sell order arrives, then $z_t < 0$, but if a buy order arrives, then $z_t > 0$). λ is the proportion of the spread due to the information asymmetry between the market maker and the informed trader, namely, the adverse selection component. θ is the amount of order persistence, ε_t and η_t are uncorrelated white noise disturbance terms.

2.5 The Madhavan et al. (1997) model

The model developed by Madhavan, et al. (1997) allows for the estimation of the adverse selection component and a trading friction component that captures both inventory and order processing costs. Order flow is assumed to exhibit first order autocorrelation (ρ) and trades can take place within the quotes with a probability equal to θ. MRR shows that transaction price changes can be a formally defined conform formulation (8).

$$\Delta P_t = \alpha + (\phi + \lambda)Q_t - (\phi - \rho\lambda)Q_{t-1} + \mu_t. \tag{8}$$

where Q_t is the trade indicator variable that now takes on a zero value if the trade is within the quotes, α captures the constant drift in prices and μ_t is a composite error term that captures both the change in price due to new information and errors due to price discreteness. The parameter vector (α, θ, ϕ, λ, ρ) is estimated using the generalized method of moments (GMM). Under this framework, the implied spread can be computed as S = $2(\theta + \phi)$. When the adverse selection and the market friction components are computed as a percentage of the spread, the two components can be expressed as $2\theta/2(\theta + \phi)$ for order processing costs and $2\phi/2(\theta + \phi)$ for adverse selection costs.

2.6 The Huang and Stoll (1997) model

The Huang and Stoll (1997) model uses a transaction approach that facilitates serial correlation in trade flows to determine the components of the spread. This model is an improvement upon Stoll (1989) that nests most of the spread decomposition models already discussed. This model also captures all three components of the spread (adverse selection cost, the inventory holding cost, and the order processing cost). Therefore, the authors propose estimating simultaneously two equations that capture the evolution of conditional expectations regarding the direction of trades and changes in the midpoint price, respectively. Such formulations are as follows:

$$E(Q_{t-1}|Q_{t-2}) = (1-2\pi)Q_{t-2}, \tag{9a}$$
$$\Delta M_t = (\alpha+\beta)(S_{t-1}/2)\ Q_{t-1} - \alpha(1-2\pi)(S_{t-2}/2)\ Q_{t-2} + \varepsilon_t. \tag{9b}$$

where Q_t is the buy-sell indicator for the transaction price P_t, and π is the probability that the trade at time t is opposite in sign to the trade at $t–1$. M_t is the midpoint of the quote that prevails just before the transaction at time t. S_t is the posted spread immediately prior to the transaction at time t. α is the percentage of the half spread attributable to the adverse selection costs and β is the inventory cost. The order processing cost is equivalent to $(1 – \alpha – \beta)$. The model is estimated using GMM.

3. Method

To verify the spread composition in the Brazilian market at intraday frequency, we use data of all stocks that compose the Ibovespa, which is the market index. Accordingly, we have data for the 69 more relevant stocks in terms of negotiability in the Brazilian market. With respect to time, the sample is composed of 10-minute quotes between January 14, 2013 and March 19, 2013. In Brazil, the market opens at 10 a.m. and closes at 5 p.m., with an aftermarket until 6 p.m. This sample is inserted in the context of the current Eurozone debt crisis so that relevant factors not present in calm periods can be identified. It is noteworthy that practically all stocks have quotations in each ten-minute period in the sample. While there are some exceptions, they are not enough to unbalance the panel of data. This fact reflects that the Brazilian market has reasonable liquidity in stocks that compose the market index.

For the decomposition, we choose the model of Huang and Stoll (1997), presented in subsection 2.6, because it makes a significant theoretical contribution to the spread decomposition literature. It is among the few models that allow the separate estimation of the adverse selection and inventory holding costs. The adverse selection component provides an empirical measure for the level of information asymmetry for a listed company. As the measure has found in many applications, such as asset pricing, fund management, accounting and corporate finance studies, the ability to accurately measure the adverse selection component is critical to these and future applications. Therefore, this model nests many previous models that rely on trade indicators or serial covariance in the trade flow. Other studies that have examined such issues as tick size have adapted its theoretical framework and the true equilibrium spread.

Regarding the variables, for each stock and interval of ten minutes, we use as a proxy for bid-ask spread (S) the range between the maximum and minimum prices. For the midpoint (M), we use the mean between such maximum and minimum quotes. For the buy-sell indicator for the transaction price (Q), we use the values of 1 if the closing price is closer to the maximum (bid side) and -1 if the closing price is closer to the minimum (ask side). Finally, for the probability that the trade at time t is opposite in sign to the trade at $t–1$ (π), we consider two approaches: an empirical estimation, i.e., the ratio between the frequency of changes in the signal of Q and all observations, and the estimation of an ordinary least squares (OLS) linear regression (9a). As the two approaches lead to similar results, we present those based on the regression because they are closer to the original proposal of Huang and Stoll (1997).

With these variables computed for each stock and period, we estimate the equation (9b) using OLS regression. Keeping the notation, to obtain the coefficients, which represent the proportion of spread components, we rearrange the equation (9b). Thus, we estimate the components of the bid-ask spread for the 69 stocks according to the regression model derived in formulation (10).

$$\Delta M_t = \alpha[(S_{t-1}/2)\, Q_{t-1} - (1-2\pi)(S_{t-2}/2)\, Q_{t-2}] + \beta[(S_{t-1}/2)\, Q_{t-1}] + \varepsilon_t. \qquad (10)$$

With the estimated parameters, we then map the structure of the bid-ask spread composition in the Brazilian market at the intraday frequency. More specifically, we conduct this analysis based on descriptive statistics of the composition along stocks as well as on a visual examination of their density.

4. Results and Discussion

First, before conducting the analysis of the bid-ask spread decomposition, we describe the phenomenon that we are studying in this paper. That is, we compute the percentage spread as a proportion of the closing price of each ten-minute interval for all stocks to standardize the values. Thus, we present in the plots of Figures 1 and 2 the means of such percentage spreads for each period and stock, respectively.

The plot in Figure 1 indicates that there is a relatively stable pattern in the temporal evolution of the means of the percentage bid-ask spread. The values oscillate around 0.5% of the closing price, with a clear seasonal effect linked to the opening and closing of the Brazilian market. Complementing this finding, the plot in Figure 2 indicates that there are differences in the mean bid-ask spread among the stocks. Despite the fact that these are all relatively liquid stocks, some exhibit greater means than others. Hence, even in the set of liquid stocks, there is still heterogeneity, a feature that is much more common in emerging markets. Such discrepancies motivate our decomposition analysis because it is plausible to find some patterns distinct from those found in emerging markets. We exhibit in Table 1 some descriptive statistics of the aggregated percentage bid-ask spreads.

The descriptive results clearly confirm the visual analysis of the plots in Figures 1 and 2. The range of the percentages of bid-ask spreads is from zero to 8.2%, indicating that despite the global mean of this variable being 0.45%, more extreme values can occur. This mean is slightly less than that found by Menyah and Paudyal (2000) for one-minute quotations of the stocks in the British market index. Such specific situations include the fact that the spread is much larger than the mean, leading to a strong positive asymmetry, as confirmed by the skewness of the coefficient, while dispersion is not significant with a standard deviation of 0.38%. Thus, as most values are close to the mean, they do not avoid the leptokurtic behavior expressed by the kurtosis coefficient. Therefore, even in the reality of concentrated percentage spreads, there are still occasions where this variable falls far from the expected value. This pattern is possibly due to the outliers identified in previous figures as such outliers mainly occur when the market opens and closes.

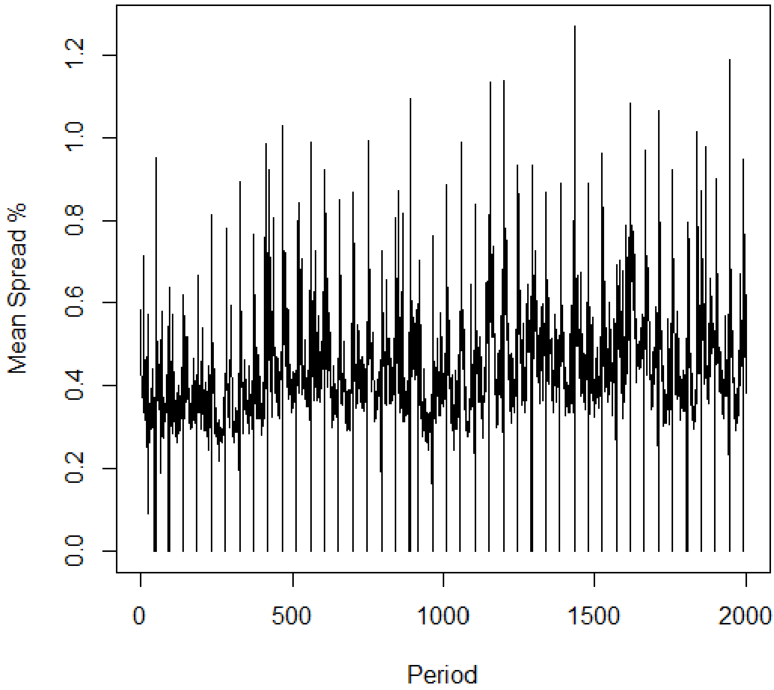

Figure 1 – Mean of the percentage bid-ask spread for each ten-minute period in the sample.

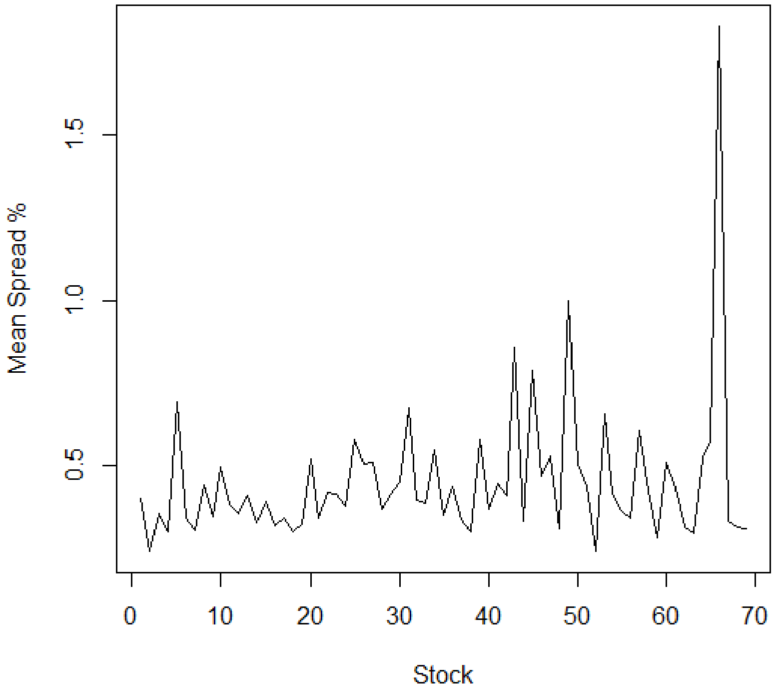

Figure 2 – Mean of the percentage bid-ask spread for stock in the sample.

Table 1 – Descriptive statistics of the percentage bid-ask spread for all stocks and ten-minute periods.

Statistic	Value
Minimum	0.00
Maximum	8.22
Mean	0.45
Standard Deviation	0.38
Skewness	3.06
Kurtosis	4.69

After this initial analysis, we present the main results obtained through the methodological procedures explained in the previous section. Thus, by applying the Huang and Stoll (1997) decomposition model for each stock during our ten minute intraday frequency sample, we derive the decomposition structure regarding the three components: adverse selection costs, inventory holding costs and order processing costs. We present in Table 2 the descriptive statistics regarding the obtained results for each component in all stocks of the sample, and we present in Figures 3 to 5 the density plots of the proportion of each component, thus providing a visual summary.

Table 2 – Descriptive statistics of the percentage of bid-ask spread components obtained from the estimation of the Huang and Stoll (1997) model.

Statistic	Adverse Selection	Inventory Holding	Order Processing
Minimum	0.01	16.56	18.24
Maximum	13.37	68.38	79.71
Mean	3.34	51.84	44.82
Standard Deviation	2.72	7.29	8.30
Skewness	1.48	-1.46	0.26
Kurtosis	2.39	9.25	7.47

With respect to the proportion of adverse selection costs, it is important to note that it has the smallest participation in the bid-ask spread of the stocks in the Brazilian market for our sample and frequency. The mean of its participation is approximately 3% with a deviation of approximately 2%. With a range from 0% to 13%, this component is positively skewed mainly because the mean is close to the minimum value of zero, though are a few large exceptions, with little probability in the tails, as noted by the value of the kurtosis coefficient.

This proportion for the adverse selection component indicates that for the stocks that are the most liquid, once they compose the market index, the intraday bid-ask spreads in the Brazilian market are not caused by information asymmetry. Moreover, the mean participation of approximately 3% is in consonance with the work of Henker and Wang (2006), who applied the same decomposition model to the US market. Nonetheless, such a component also assumes negative values in the Huang and Stoll (1997) model, which is as a drawback to the approach. Clarke and Shastri (2000) find negative values for approximately 60% of the NYSE stocks in their sample, while Van Ness et al. (2001) report negative values for over 50% of their sample. In this regard, our findings contradict these authors because for all stocks, this component reflects positive participation.

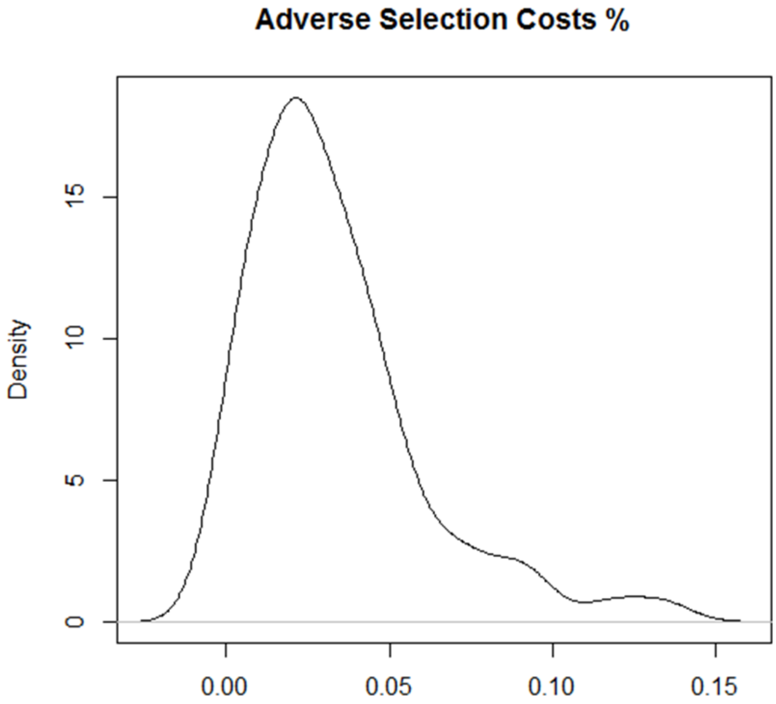

Figure 3 – Density of the percentage of the adverse selection costs in the composition of the bid-ask spread of the studied stocks.

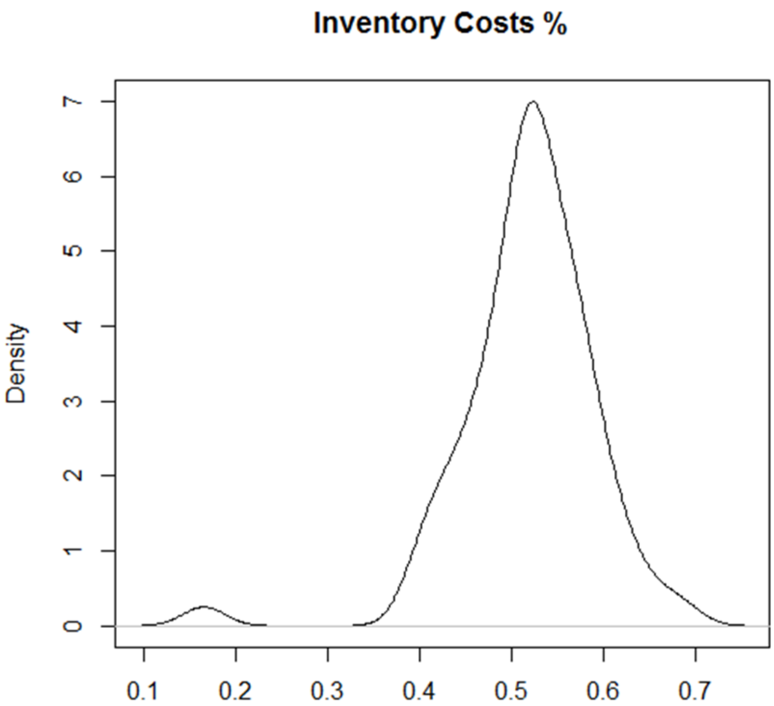

Figure 4 – Density of the percentage of the inventory holding costs in the composition of the bid-ask spread of the studied stocks.

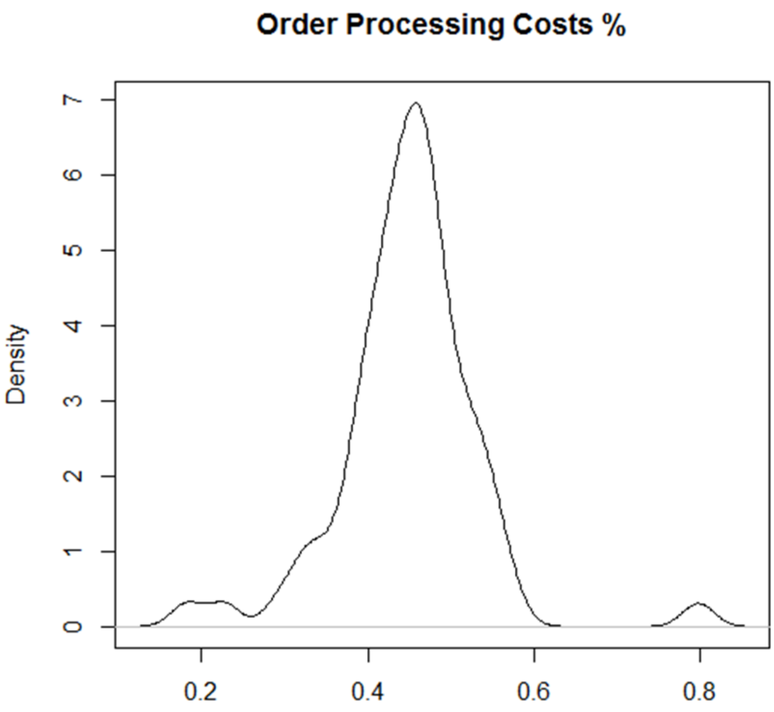

Figure 5 – Density of the percentage of order processing costs in the composition of the bid-ask spread of the studied stocks.

With respect to the inventory holding costs, the obtained results indicate that in the Brazilian market for intraday frequency, this component is, according to the mean, the one with the greatest participation in the bid-ask spread. The mean participation of this component in the sample is approximately 52% with a relatively small deviation of 7%. Therefore, the range of values is substantial, from 16% to 68%, leading to an important presence of cases in the tails, as noted by the leptokurtic behavior. The values of the range also help to explain the negative asymmetry, once the minimum is much farther away from the mean than the maximum. This result is relevant because this component is linked primarily to liquidity issues, a problem that is typical in emerging markets. For comparison, Stoll (1989), Huang and Stoll (1997) and Bollen et al. (2004) find that inventory holding costs account for 10%, 28.7% and 29.28%, respectively. All of these studies are conducted in the US market.

Finally, we analyze the results obtained for the order processing costs component. Too many papers, especially those that apply the Huang and Stoll (1997) model, neglect this component because their estimation is indirectly implicit from the other two factors. However, it is crucial to understand that the order processing costs proportion also includes factors that are not explained by the adverse selection and inventory holding components. Thus, for our sample, this component corresponds in mean to approximately 45%, with a deviation of 8%. In comparison with the other two components, the pattern is more symmetric mainly because of the substantial range, which varies from 18% to 80%. This large range leads to extreme values, as noted by the kurtosis coefficient.

To give more robustness to the results, we replicate these procedures, but rather than using the whole sample, we split the stocks according to the disclosure of information through a corporate governance indicator present in the Brazilian market. The idea behind this division is that stocks from companies that divulge more information are less affected by an adverse selection component. Nonetheless, the results are practically the same for the two groups, indicating that these liquid stocks exhibit a homogenous behavior.

5. Conclusion

In this paper, we aim to identify the bid-ask spread components in the Brazilian market at intraday high frequency. To do so, we use data of all stocks that compose the Ibovespa, at 10-minute frequencies, from January to March of 2013. We use the model of Huang and Stoll (1997) as it allows for the separate estimation of the adverse selection and inventory holding costs, and it nests many previous models. Preliminary results indicate that there is a relatively stable pattern in the temporal evolution of the means of the percentage bid-ask spread, with values oscillating around 0.5 % of the closing price, with a clear seasonal effect linked to the opening and closing of the Brazilian market.

With respect to the proportion of components, adverse selection costs exhibit a small level of participation in the bid-ask spread of the stocks in the Brazilian market (approximately 3%), while inventory holding costs demonstrate the greatest participation (approximately 52%), This is then followed by order processing costs component (45%). The presented results elucidate the importance of liquidity over information asymmetry. Despite both issues being more prominent in emerging markets, with respect to the bid-ask spread, the predominance is for liquidity. Our findings better elucidate this pattern in the Brazilian market. For instance, Menyah and Paudyal (2000), using data from stocks of the British index market, find that the bid-ask spread composition is 47%, 23% and 30% from adverse selection, inventory holding and order processing costs, respectively, thus emphasizing that liquidity is a much more relevant problem in emerging markets than it is in developed markets.

This study is a first attempt to map the bid-ask spread composition in the Brazilian market. For future research, it is important to better understand the factors that govern such composition. Thus, we suggest that after decomposing the spread, market and economic variables should be used to explain the components in an isolated way. Furthermore, discrimination between periods and market events can highlight too many relevant patterns, thus helping investors trade in the Brazilian market as they have more information.

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