Corwin-Schultz bid-ask spread estimator in the Brazilian stock market

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Abstract

This paper tests the validity of Corwin-Schultz bid-ask spread estimator in the Brazilian stock market. The Corwin-Schultz estimator arises as an easy way to compute asymmetric information throughout daily high and low stock prices for estimating overnight and non-negative adjusted spreads. The sample is represented by the *Ibovespa* firms from 1986 to 2014 and was analysed with time series econometrics. The findings show that the measures of spread have stationarity properties, allowing for forecasting in a period lagged variables, besides having the property of time varying cointegration to market-to-book ratio, debt on equity, size and return and also presenting sensibility to different periods, industries and listing segments. Thus, Corwin-Schultz bid-ask spread estimator seems to be a valid and reliable measure for forecasting aggregate data variables through the weighted average of firm level variables.

Keywords: Corwin-Schultz bid-ask spread estimator; Asymmetric information; Market microstructure; Time varying cointegration.

1. Introduction

Comprehending how information is obtained and disseminated is essential to understand how economies function (Rosser Jr, 2003) as well as how it affects price movements (Muth, 1961; Cuthbertson & Nitzche, 2004).

Information asymmetry occurs when one trader has more or better information than another, and this asymmetry influences market equilibrium (Akerlof, 1970) and improving the quality of information of uninformed traders throughout the signalling issues (Spence, 1973), thus showing that competition in markets with imperfect information is more complex than assumed in classical economics. This complexity is because competitors may limit the purchases of their customers and competitive equilibria are not Pareto optimal (Rothschild & Stiglitz, 1976). In particular, for stock markets, as Grossman and Stiglitz (1980) show, the only way for informed traders to earn abnormal returns is to take better positions than uninformed ones, because trade activity causes private information to influence prices, although imperfectly.

However, asymmetric information occurs in the trading activity of stock markets along with order processing and inventory holding costs, and sometimes it could be difficult to distinguish between them, but the effects of adverse selection/asymmetric information have been found to be a significant part of the spread between bid-ask quotes (Huang & Stoll, 1997). The behaviour of these components is quite different as well. Adverse selection has been found to increase when earnings announcements are expected, but order processing and inventory holding have been found to decrease (Krinsky & Lee, 1996).

Minardi, Sanvicente, and Monteiro (2006) showed the absence of order processing and inventory holding costs and the presence of asymmetric information costs in the Brazilian stock market. Therefore, for the present study, we directly treat bid-ask spread as asymmetric information.

Furthermore, this study considers that asset prices are driven by equality between purchase and sales flows rather than demand and supply issues. Therefore, we use an information-based model, focusing on asymmetric information and assuming that market makers cannot observe the origin of orders (Bailey, 2005).

In this study, we investigate the validity of the bid-ask spread estimator (Corwin & Schultz, 2012a) as an easy-to-compute and alternative measure of asymmetric information in the Brazilian stock market. The relevance of this type of research model increases because the high-frequency data used to obtain another measure of asymmetric information are available only recently (Easley, Hvidkjaer, & O´Hara, 2002; Martins & Paulo, 2013).

Minardi, Sanvicente, and Monteiro (2006) developed and tested a measure for bid-ask spread in the Brazilian stock market from 1998 to 2003. Their findings showed that bid-ask spread is correlated negatively with liquidity and positively with return. Data of the biggest firms were analysed by them using correlation and ordinary least squares (OLS) estimation methods.

In this study, we analyse the aggregate daily high and low stock prices data of the most traded shares on the Brazilian stock market from 1986 to 2014. The Corwin-Schultz measures of asymmetric information are stationary and can be forecast using single-equation dynamic modelling (Granger, 1981). The aggregate data are obtained from the weighted average of the firm-level Ibovespa components' data for the second quarter of 2014.

The results are consistent with those of other studies examining the same market (Martins, Paulo, & Albuquerque, 2013) and market microstructure theory (Easley, Hvidkjaer,

& O´Hara, 2002). The measures are sensitive to different periods, industries, and listing segments and have a time-varying cointegration vector with firm-level characteristics.

The remainder of this paper is structured as follows. The next section presents the theoretical framework comprising the market microstructure theory, the probability of information-based trading measure (PIN) score, and Corwin–Schultz issues. The third section describes the sample and the time-series techniques applied. The fourth section presents and discusses the findings, and the final section presents the main implications and concluding remarks.

2. Theoretical Framework

2.1 Market microstructure

Hasbrouck (2007) identified the electronic limit order book, asymmetric information, and linear time-series analysis as the prominent trading approaches used to study financial securities or the market microstructure. Madhavan (2000) conceptualizes market microstructure as the financial area pertaining to the process by which the latent demands of investors ultimately translate into transactions. The author clarifies the importance of market microstructure and informational economics and identifies the links between the former and the fields of investment, financing, and capital structure. For market microstructure theory, asset prices need not reflect the full-information expectation values due to a variety of frictions driven by the rapid structural, technological, and regulatory changes affecting the securities industry world-wide. Hasbrouck (2007) argues that the microstructure perspective of security price dynamics shifts from monthly or daily to a minute or second horizon, and that theoretically market microstructure has two main types of asymmetric information models—sequential trade models wherein the trader is independently, sequentially, and randomly selected, and strategic trade models wherein a single informed agent trades at multiple times—both having the essential feature of revealing some of the agent's private information.

Roll (1984) presented a method to infer the effective bid-ask spread that requires only the securities time-series' prices, assuming the market efficiency and stationarity of observed price changes. The effective bid-ask spread can be estimated with the equation $Spread = 2\sqrt{-cov}$, where 'cov' is the first-order serial covariance of price changes. This method came to be known as the Roll serial covariance bid-ask estimator, following Harris (1990), who examined its statistical properties and argued that Roll's method has a small sample estimator bias whereas French and Roll's (1986) adjusted-variance estimator ($Spread = Var + 2\ cov$) is unbiased but noisy. The latter method was proposed by French and Roll (1986) while examining the greater variances in trading hour than non-trading hour returns. Glosten and Milgron (1985) believed that bid-ask spread implies a divergence between the observed and realizable returns and that the observed returns are approximately the realizable returns plus what the uninformed anticipate when losing to insiders. Glosten and Harris (1988) proposed, estimated, and cross-validated a two-component asymmetric information spread model, while decomposing the bid-ask spread into asymmetric information and inventory costs components. They found the spread to be a function of trade size.

Hasbrouck (1988) examined the effects of asymmetric information and inventory control on the relation between trades and quote revisions, and found substantial information on trade and strong evidence that large trades conveyed more information than small trades. Hasbrouck (1996) further examined the information on automated orders by using an econometric model capturing the joint behaviour of automated orders and the return on stock index futures, and found that orders contain information useful in predicting stock returns beyond the information contained in the reported trades. In another paper, Hasbrouck (1999) proposed a dynamic bid-ask quotes model incorporating the microstructure effects arising from the manner in which security is traded, such as the stochastic cost of market-making, discreteness, and clustering, using the Gibbs sampler as convenient estimation vehicle.

Hasbrouck and Seppi (2001) found that bid-ask spread and quote sizes help explain the time variation in trade impacts, and that the existing common factors can explain the common variation in signed and absolute returns. Hasbrouck and Saar (2009) examined a sample trading in a limit order book and observed that over one-third of non-marketable limit orders are cancelled within two seconds. Investigating the role of these orders in the market, they found evidence consistent with the dynamic trading strategies whereby traders follow market prices or search for latent liquidity.

Roll and Subrahmanyam (2010) found that the bid-ask spreads in equities decline on average but become increasingly right-skewed, even when controlling for size, price, and volume, consistently, with more competition among market makers, and that the skewness is also cross-sectionally related to information proxies such as institutional holdings and analyst following. Roll, Schwartz, and Subrahmanyam (2014) found that signed and absolute trading activity in contingent claims predicts shifts in aggregate state variables as well as signed and absolute returns around major macroeconomic announcements.

Hasbrouck and Saar (2013) proposed the *RunsInProcess*, a measure of low-latency activity used to investigate the impact of high-frequency trading on the market environment using publicly available data, suggesting that millisecond environment constitutes a fundamental change from the manner in which stock markets operated.

2.2 PIN score

Easley, Kiefer, and O´Hara (1997) developed the PIN, which is now standard in the literature. This measure uses the price, lagged price, and number of buys and sells to identify the importance of buy and sell trade in model specification and show how such a model can be used in a well-defined statistical framework to guide empirical work (Easley, Kiefer, & O´Hara, 1997). The paper followed Easley and O´Hara's (1992) findings that trade time affects prices, with the time between trades affecting the spreads of security prices and volume affecting the speed of price adjustment. The definition of trade direction followed Lee and Ready's (1991) algorithm.

Easley, Hvidkjaer, and O´Hara (2002) used Easley, Kiefer, and O´Hara's (1997) PIN model to incorporate obtained estimates into a Fama–French asset-pricing framework, and found that such information does affect asset pricing. Hasbrouck (1991) suggested that the interactions of security trades and quote revisions can be modelled as a vector autoregressive system. The model estimation results showed that the full price impact of trade comes only with a protracted lag, the impact is a positive and concave function of the trade size, large trades widen the spread, trades occurring following wider spreads have larger price impacts, and information asymmetries are more significant for smaller firms. Easley and O`Hara (1991) showed that the market maker who knows the type and composition of trades can set larger spreads and adjust prices faster than if price-contingent orders were not allowed, and confirmed the important policy implications of distinction between variance and episodic price volatility. Blume, Easley, and O´Hara (1994) showed that volume provides information on quality that cannot be deduced from the price statistic; how volume, information precision, and price movements relate; and how sequences of volume and prices can be informative. They concluded that technical analysis arises as a natural component of the agents' learning process. Easley *et al.* (1996) found that the probability of information-based trading is lower for high-volume stocks and provided evidence of the economic effect of information-based trading on spreads.

Easley, O´Hara, and Srinivas (1998) developed an asymmetric information model wherein informed traders can trade in option or equity markets and tested the model's hypotheses with intraday option data. They found that negative and positive option volumes contain information on future stock prices. Dufour and Engle (2000) tested and estimated the role played by waiting time between consecutive transactions in the process of price formation using Hasbrouck’s (1991) vector autoregressive (VAR) system, and found a negative association between waiting time, price impact of trade, speed of price adjustment to trade-related information, and the autocorrelation of signed trades. O´Hara (2003) developed an asymmetric information asset-pricing model incorporating the transaction costs of liquidity and risks of price discovery and examined the implications of market microstructure for asset pricing. Easley and O´Hara (2004) investigated the role of information in a firm’s cost of capital and concluded that investors demand a higher return on stocks with greater private information. Agarwal and O´Hara (2006) found that the PIN drives the capital structure, with companies having higher extrinsic asymmetric information more probable to increase their leverage.

Hasbrouck (2007, p. 42) argues that agents always face the same spread, which represents the costs of security necessary for trading in securities. Chan, Mankveld, and Yang (2008) constructed information asymmetry measures for equity pricing in the local A-share and foreign B-share Chinese markets following Easley, Kiefer, and O´Hara (1997), and found that they explain a significant portion of the cross-sectional variation in B-share discounts even after controlling for other factors.

Martins and Paulo (2013) applied Easley, Hvidkjaer, and O´Hara’s (2002) PIN model to estimate the asymmetric information level of the Brazilian stock market and its association with liquidity. They found an average PIN of 0.249 for 229 listed firms from 2010 to 2011 and a negative association between liquidity and PIN only for common stocks with high liquidity. In another paper (Martins & Paulo, 2014), the authors found a positive relationship between the PIN and risk, return, and liquidity of shares as well as cost of equity and size of companies and a negative relationship between the PIN and abnormal returns of shares. Martins, Paulo, and Albuquerque (2013) estimated the PIN in relation to stock returns and found a negative association between corporate governance and information asymmetry and a positive association between the PIN and stock returns. Finally, Girão, Martins, and Paulo (2014) found an average PIN of 0.229 in the Brazilian stock market, but no significant association between the PIN and an accounting variables valuation model.

2.3 The Corwin–Schultz bid-ask spread estimator

Corwin and Schultz (2012a) developed a bid-ask spread estimator from daily high and low prices to measure the bid-ask spread of shares, using an easy calculation method. The estimator is based on two assumptions. First, the daily high prices are typically buyer initiated and low prices seller initiated, and therefore the ratio of high-to-low prices for a day reflects both the fundamental volatility of stock and its bid-ask spread. Second, the volatility component of the high-to-low price ratio increases proportionately with the length of trading interval whereas the component due to bid-ask spreads does not. Throughout the simulations constructed under realistic conditions, as the authors argue, the correlation between the high–low spread estimates and true spreads is about 0.9 and the standard deviation of the high–low spread estimates is only one-half of the standard deviation of the estimates obtained from Roll's (1984) covariance spread estimator. The Corwin-Schultz bid-ask spread estimator is presented in equation (1) below, where *S* is the spread; *e* is the mathematical constant (*e* basis) of *x;* α is as shown in (2), β as in shown (3), and γ as shown in (4); and *H* and *L* denote the observed high and low stock prices, respectively.

$$S = \frac{2(e^{\alpha} - 1)}{1 + e^{\alpha}} \tag{1}$$

$$\alpha = \frac{\sqrt{2\beta} - \sqrt{\beta}}{3 - 2\sqrt{2}} - \sqrt{\frac{\gamma}{3 - 2\sqrt{2}}} \tag{2}$$

$$\beta = E\left\{\sum_{j=0}^{1}\left[ln\left(\frac{H_{t+j}^{0}}{L_{t+j}^{0}}\right)\right]^{2}\right\} \tag{3}$$

$$\gamma = E\left\{\sum_{j=0}^{1}\left[ln\left(\frac{H_{t,t+1}^{0}}{L_{t,t+1}^{0}}\right)\right]^{2}\right\} \tag{4}$$

Variable α (2) represents the difference between the adjustments of a single day and a 2-day period, β (3) represents the daily high and low price adjustments to the high price, and γ (4) represents a 2-day period high and low price adjustments. Corwin and Schultz (2012a) posit that the estimator of (1) is easy to compute and that it does not require the researcher to successively iterate estimates of the spread to get the correct value. They have provided an electronic example to confirm the proposition.

Corwin and Schultz (2012b) tested their bid-ask estimator on individual stocks of 11 countries (Hong Kong, India, Korea, Japan, Italy, France, Belgium, Sweden, the United Kingdom, Brazil, and New Zealand), and have provided estimates of the U.S. stock market and other useful applications, examples, and notes. Maskara and Mullineaux (2011) computed the Corwin-Schultz bid-ask spread (2012a) and other measures to examine the abnormal announcement returns of loans and in general did not find significant association between returns and loan announcements. However, Karstanje *et al.* (2013) found liquidity timing leading to tangible economic gains when comparing five different liquidity measures, including the Corwin–Schultz (2012a) measure. Lin (2014) modified the Corwin–Schultz (2012a) model to analyse the estimation accuracy of the high–low spread estimator and found that its performance depended on the size of the true spread, level of transaction frequency, and degree of volatility, and concluded that more empirical research is still needed to gain further evidence on the analysis. Zhang *et al.* (2014) tried to validate the Corwin-Schultz (2012a) method to predict the returns from 1926 to 2010 for the U.S. ordinary common stocks, and found the bid-ask measure lacking significantly as liquidity measure to predict returns. Cerqueira and Pereira (2014) provided evidence on the association between quality of financial reporting and information asymmetry in Europe, using discretionary accruals as a proxy for quality of financial reporting and the Corwin-Schultz (2012a) bid-ask spread estimator to measure information asymmetry, and found this measure more efficient than the closing bid-ask spread.

The PIN score reflects the probability of trading under private information. Consequently, the PIN probability price often equals the abnormal returns of informed traders. Corwin and Schultz's bid-ask spread estimator reflects the same abnormal return, but on the highest and lowest share prices instead of all trades of a day. Therefore, the PIN score and Corwin–Schultz bid-ask spread estimator figures can be directly compared. To reinforce this fact, note that the PIN score and Corwin–Schultz estimator figures give only the asymmetric information in markets without the order processing and inventory holding costs (Minardi, Sanvicente, & Monteiro, 2006).

3 Methodology

In this study, we analyse the reliability and validity (Bryman, 2012) of the alternative asymmetric information measure proposed by Corwin and Schultz (2012a) for the Brazilian stock market. Here, reliability means the stability of coefficients (the absence of abrupt structural breaks) and validity refers to the forecast of a measure (Bryman, 2012). The augmented Dickey–Fuller **(**ADF) and single-equation dynamic modelling series (Dickey & Fuller, 1979; 1981; Granger, 1981; 2010) were used to assess the stability and forecast of measures, instead of Cronbach's alpha (Cronbach & Shavelson, 2004), owing to the possible violation of several assumptions (Gu, Little, & Kingston, 2013).

Brazil is an appropriate emerging country, with its stock market reformed since 2002 (including its accounting standards), to analyse asymmetric information. Its stock market provided intraday trading data only for the last decade. Thus, Brazil can be considered suitable to research the new measure of asymmetric information for testing several financial theories.

The α, β, and γ estimates (equations 2, 3, and 4) of the Corwin–Schultz (2012a) model have been computed on the daily high and low stock prices of the constituents of Ibovespa (the Brazilian stock market weighted average of a theoretical portfolio). This index represents the shares of 68 Brazilian listed companies most traded in the second quarter of 2014 from 2 January 1886 to 2 June 2014. The sample considers only the actual level of asymmetric information in the Brazilian stock market, and not the risk of survival or other sample biases; furthermore, the true high and low prices of infrequently traded stocks are not considered (Corwin & Schultz, 2012a). Following Corwin and Schultz (2012b), the resulting estimates (S_2 and S_0) are adjusted for overnight price changes and non-negative results.

The data have been aggregated by weighted average of each share on the index, allowing for proper application of time-series techniques. All data were updated up to the second quarter of 2014 based on consumer price index to mitigate inflationary effects. The sample was intended to be wide as possible to avoid the bias of rejection of cointegration null (Timmermann, 1995). To check for robustness of the measures, we divide S_2 and S_0 into different periods, firm level industries, and listing segments. We then test the measures for time-varying cointegration with the restricted variables obtained from combining the Chebyshev time polynomials (Bierens & Martins, 2010) and the variables related to asymmetric information, such as market-to-book ratio (M/B) for growth opportunity set, debt on equity (D/E) for leverage, and size (SIZE) and stock market return (RETURN) for evolution of stock prices. While the exchange rate effects on asymmetric information of the Brazilian stock market could not be directly computed, the analysis of different periods tried to capture some of their consequences.

4 Results and Discussion

4.1 S_2 and S_0

Variables S_2 and S_0 represent Corwin and Schultz's (2012b) overnight and non-negative adjusted bid-ask spread estimator respectively. The average daily spreads for S_2 and S_0 are 0.006 and 0.016, and these lead to average monthly spreads of 0.13 and 0.34, respectively (see Table 1). While the average monthly value of 0.249 is almost consistent with that of Martins and Paulo (2013), the monthly average for 2010–2011 is higher.

The average S_2 and S_0 estimate is consistent with the Corwin–Schultz (2012b) estimate of S_0 for Brazil from 1993 to 2007 (0.0131). These are consistent with Minardi, Sanvicente, and Monteiro's (2006) results, which varied from 0.0131 to 1.1369 depending on the frequency. A comparison of these results shows that S_2 and S_0 have properties similar to other asymmetric information measures, as pointed out by Karstanje *et al.* (2013). It also confirms Hasbrouck's (2007) proposition that asymmetric information and linear time-series analysis are prominent market microstructure topics.

Table 1

Descriptive Statistics

Variable	N. Obs.	Min.	Mean	Max.	Std. Dev.
Α	114	-0.0220	0.0065	0.0308	0.0100
Β	114	0.0007	0.0035	0.0153	0.0028
Γ	114	0.0007	0.0034	0.0161	0.0029
S_2	114	-0.0220	0.0065	0.0308	0.0100
S_0	114	0.0068	0.0168	0.0419	0.0055
S_2_Month	114	-0.4410	0.1351	0.6383	0.2050
S_0_Month	114	0.1512	0.3445	0.8669	0.1131

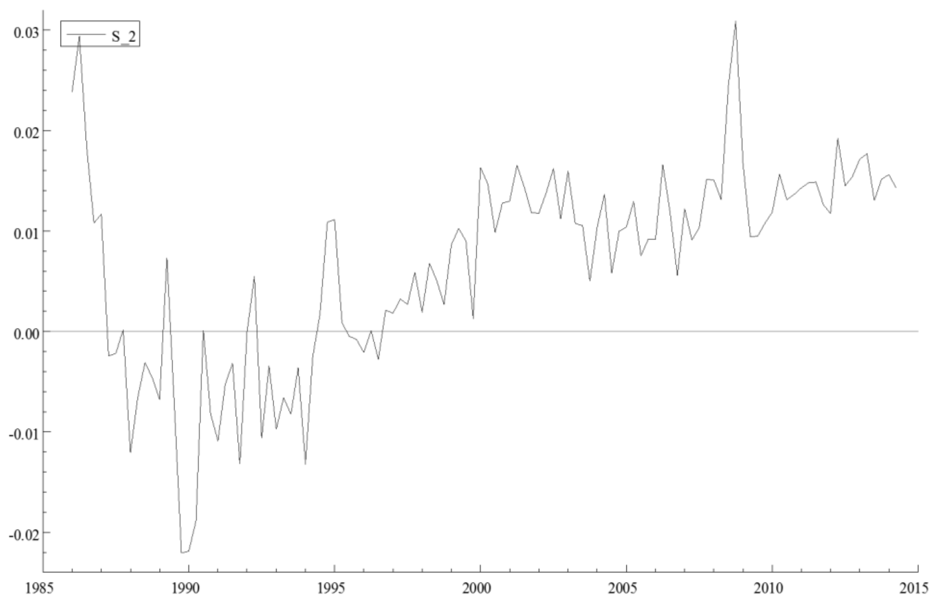
Note: The table presents the descriptive statistics of the Corwin–Schultz (2012a) model's variables α, β, and γ, which have been presented in equations (2), (3), and (4); S_2 is the pure spread and S_0 the non-negative spread, and both are adjusted to overnight returns. Source: The author.

The spreads were higher for either S_2 or S_0 during the 2008 financial crisis. Minardi, Sanvicente, and Monteiro (2006) found different spreads for volume and turnover, which is consistent with the changes observed in S_2 and S_0 for the financial crisis period.

The behaviour of asymmetric information in Brazil is presented in Figures 1 and 2, to complement the descriptive statistics. Figure 1 presents the S_2 values for the analysed period. The maximum and minimum values can be easily detected, whereas the range (-0.02 to 0.03) and slope suggest that S_2 could be stationary with a trend. Stationarity is suggested for S_0 as well, which is presented in Figure 2.

Figure 1

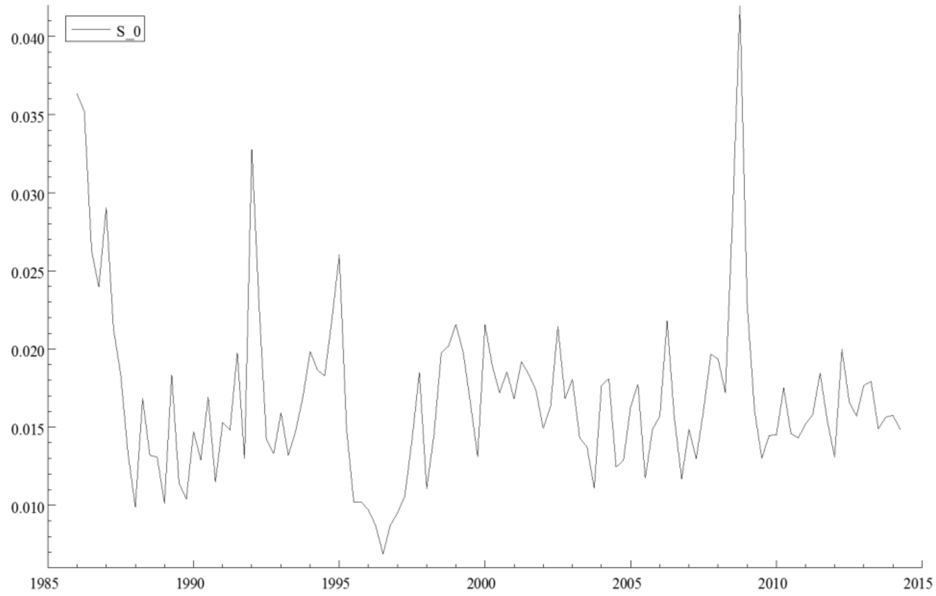
The Corwin–Schultz spread in the Brazilian stock market



Note: The figure presents the time-series of the pure and overnight return-adjusted spread of the Corwin–Schultz (2012a) model for the Brazilian stock market. Source: The author.

Figure 2

The Corwin–Schultz non-negative spread in the Brazilian stock market



Note: The figure presents the time-series of the non-negative and overnight return-adjusted spread of the Corwin–Schultz (2012a) model for the Brazilian stock market. Source: The author.

The stationarity of S_2 and S_0 have been confirmed in unit root tests (Dickey & Fuller, 1979; 1981), with strong statistical significance in the three periods of lagged variables (Table 2), indicating that S_2 and S_0 have no other determinants.

Table 2

Unit root tests

S_2								
D-lag	t-adf		beta Y_1	sigma	t-DY_lag	t-prob	AIC	F-prob
3	-4.8720	***	0.5478	0.0053	0.2980	0.7663	-10.40	
2	-4.9010	***	0.5518	0.0052	-1.6840	0.0953	-10.42	0.7663
1	-5.4630	***	0.5126	0.0053	-0.4266	0.6705	-10.41	0.2396
0	-6.2100	***	0.4970	0.0053			-10.42	0.3839

S_0								
D-lag	t-adf		beta Y_1	sigma	t-DY_lag	t-prob	AIC	F-prob
3	-4.3680	***	0.5232	0.0043	-0.5038	0.6155	-10.79	
2	-4.7150	***	0.5078	0.0043	-0.7554	0.4517	-10.81	0.6155
1	-5.4220	***	0.4778	0.0043	0.1885	0.8509	-10.82	0.6646
0	-6.1020	***	0.4864	0.0043			-10.84	0.8360

Note: The table presents the ADF unit root tests (Dickey & Fuller, 1979; 1981) for S_2 and S_0 of the Corwin–Schultz (2012a) model in the Brazilian stock market, showing constant, trend, and seasonal dummies (ADF tests -T = 110, Constant + Trend + Seasonals; 5% = -3.45, 1% = - 4.04). Source: The author.

Statistical significance: *** - 0.01.

The unit root test results show another consequence. The possibility of endogeneity seems to be circumvented from the assumption that a stationary variable can be explained only by itself. This fact maintains the strong classical linear regression model assumptions and mitigates the possibility of bi-directional causality feedback (Asteriou & Hall, 2011). Even for the cointegration analysis in the next section, the stationarity of S_0 and S_2 suggests that they are the driving force behind the control variables.

However, endogeneity is always a relevant issue because of biased estimates. We examine S_0 and S_2 individually in the unit root tests, but find no way to relate to another variable. Vector autoregressive models abandon the distinction between endogenous and exogenous variables and treat all variables as endogenous (Asteriou & Hall, 2011). For long-run relationships, the variables in the model can form several equilibrium relationships governing the joint evolution of all variables (Asteriou & Hall, 2011), making endogeneity an assumption of time-series analysis.

Stationarity results show that the studied measures are stable and can be forecasted (Bryman, 2012). This finding is consistent with Martins, Paulo, and Albuquerque (2013), who found that asymmetric information is an independent variable determining asset returns, and non-consistent with Martins and Paulo (2014), who found that asymmetric information is determined by risk, return, abnormal returns, liquidity, cost of equity, and size.

The finding is also consistent with Easley, Hvidkjaer, and O´Hara (2002), who show the determination of asset returns by asymmetric information.

The findings of Maskara and Mullineaux (2011) strengthen the stationarity finding, because they did not find any association between the Corwin–Schultz (2012a) and abnormal returns. Karstanje *et al.* (2013) considered S_2 and S_0 as proxies for liquidity and did not find the robust predictive ability of liquidity for forecasting asset returns, which is neutral related to stationarity finding, exactly as in Zhang *et al*. (2014).

Cerqueira and Pereira (2014) show the association between the Corwin–Schultz measure and quality of financial reporting in Europe. Their findings strengthen the power of the Corwin–Schultz measure as asymmetric information measure, but go against the stationarity finding because poor quality of financial reporting generates asymmetric information.

Lin (2014) argues that the accuracy of the Corwin–Schultz (2012a) measure depends on the size of spread, transaction frequency, and degree of volatility. From Figures 1 and 2, the degree of volatility appears to imply a break in stability of measure, but the modelling process of S_2 and S_0 (see Tables 3 and 4 and Figures 3 and 4) results in the absence of strong structural breaks (Chow, 1960). Spread size and transaction frequency issues could be solved through aggregate data analysis.

The forecasting of S_2 and S_0 was carried out using the single-equation dynamic modelling of Granger (1981) and OLS estimation.

Model selection has shown that the optimum specification belongs to the model with lagged variables in one period (Tables 3 and 4).

The S_0 forecasting process used only a constant and lagged variable, whereas the S_2 model was specified with a trend. Goodness of fit can be checked in Figures 3 and 4.

Therefore, on an aggregate basis, we can expect variance of asymmetric information in the Brazilian stock market. The prediction of asymmetric information is a novelty because other authors have not examined it in this manner (Minardi, Sanvicente, & Monteiro, 2006; Girão, Martins, & Paulo, 2014; Martins & Paulo, 2013, 2014).

Table 3

Modelling S_2 using the OLS method

	Coefficient	Std. Error	t-value	t-prob	Part.R^2
S_2_1	0.5231	0.0754	6.9300	0.0000***	0.3098
Constant	-0.0037	0.0012	-3.0600	0.0028***	0.0806
Seasonal_2	-0.0010	0.0011	-0.8510	0.3964	0.0067
Trend	0.0001	0.0023	5.0600	0.0000***	0.1930

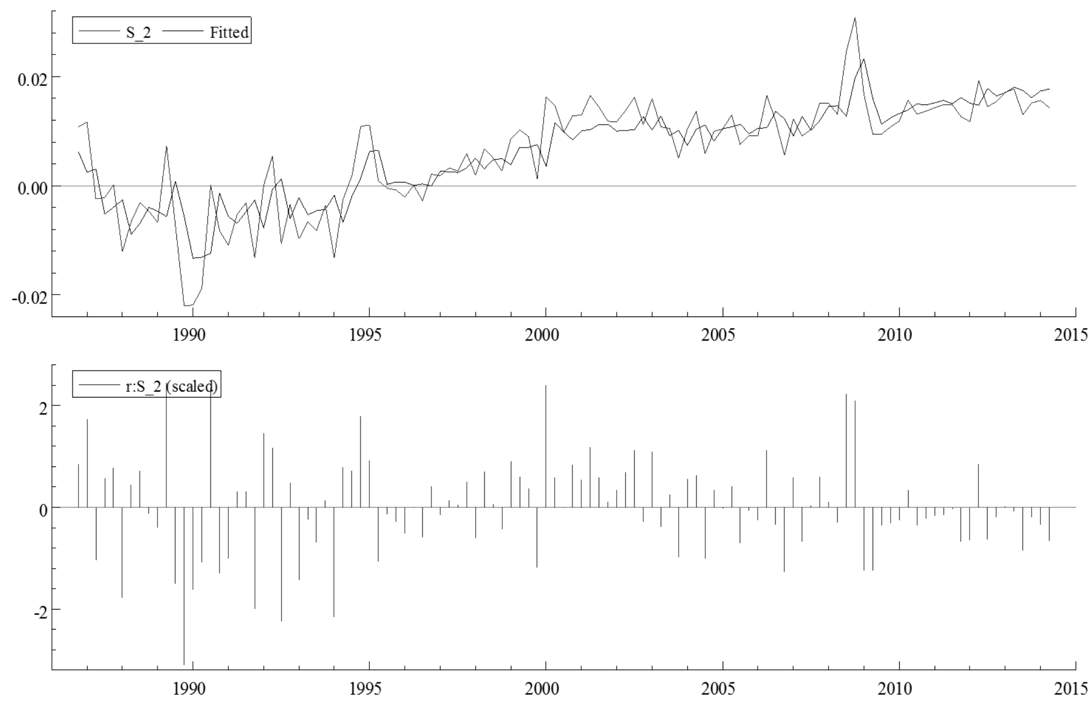
Sigma	0.0053	RSS	0.3011
R^2	0.7162	F(3,107)	90.040 [0.000]***
Log-likelihood	426.0730	DW	2.09
No. of observations	111	no. of parameters	4
Mean (S_2)	0.0061	var(S_2)	9.56201e-005

Note: The table presents the forecasting final model of S_2 computed using the single-equation dynamic modelling of Granger (1981) for the Brazilian stock market. Source: The author.

Statistical significance: *** - 0.01.

Figure 3

Fitted values of S_2



Note: The figure presents the S_2 forecasting final model's fitted values computed by ordinary least squares in the Brazilian stock market. The lower part of figure shows the model residuals. Source: The author.

Table 4

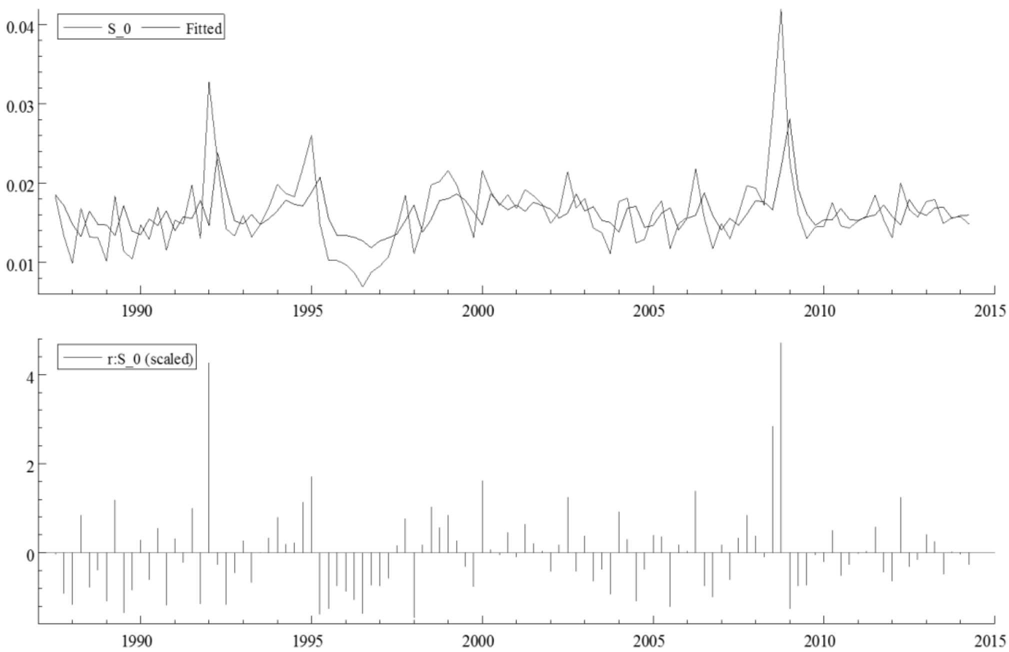
Modelling S_0 by OLS

	Coefficient	**Std. Error**	**t-value**	**t-prob**	**Part.R^2**
S_0_1	0.4638	0.0855	5.4200	0.0000***	0.2173
Constant	0.0086	0.0014	5.9800	0.0000***	0.2520
Sigma	0.0042		RSS		0.1901
R^2	0.2172		F(1,106)		29.43[0.000]***
log-likelihood	437.9030		DW		1.95
no. of observations	108		no. of parameters		2
mean(S_0)	0.0161		var(S_0)		2.2495e-5

Note: The table presents the forecasting final model of S_0 computed using single-equation dynamic modelling of Granger (1981) for the Brazilian stock market. Source: The author.
Statistical significance: *** - 0.01.

Figure 4

Fitted values of S_0



Note: The figure presents the S_0 forecasting final model's fitted values computed by ordinary least squares and in the Brazilian stock market. The lower part of figure shows the model residuals. Source: The author.

The forecasting of asymmetric information is consistent with the theoretical framework. It shows a feasible asset mispricing (Akerlof, 1970) and helps uninformed traders obtain better information (Spence, 1973) besides abnormal returns, and diminish the consequences of private information trading on their portfolios.

4.2 Robustness check

A segregation of time subsamples (Table 5) shows that the average of S_2 increased following the Brazilian stock market reform, which introduced four different share listing segments (Rabelo & Vasconcelos, 2002). This finding in a non-consistent sense represents stock market development theory (Demirgüc-Kunt & Maksimovic, 1996; Demirgüc-Kunt, Feyen, & Levine, 2013). Variable S_2 also became closer to a non-negative measure. The mean of S_O presented a peak in 2008–2009, consistent with the financial crisis. The exchange-rate regime is seen to have become flexible in 1999, which could be strongly related to the S_2 figures, with averages roughly half of the 2000–2007 mean figures. Political variables also can explain such asymmetric information movements.

Table 5

Subsamples of S_2 and S_0

			S_2		
Subsample	**N. Obs.**	**Min.**	**Mean**	**Max.**	**Std. Dev.**
1986:1–1989:4	16	-.0220	.0021	.0293	.0136
1990:1–1994:2	18	-.0218	-.0074	.0054	.0068
1994:3–1997:4	14	-.0027	.0024	.0111	.0042
1998:1–1999:4	8	.0012	.0056	.0102	.0034
2000:1–2007:4	32	.0050	.0116	.0165	.0031
2008:1–2009:4	8	.0094	.0162	.0308	.0077
2010:1–2014:2	18	.0117	.0147	.0192	.0019

			S_0		
Subsample	N. Obs.	Min.	Mean	Max.	Std. Dev.
1986:1–1989:4	16	.0098	.0191	.0363	.0087
1990:1–1994:2	18	.0114	.0167	.0327	.0049
1994:3–1997:4	14	.0068	.0134	.0260	.0057
1998:1–1999:4	8	.0110	.0170	.0215	.0038

2000:1–2007:4	32	.0110	.0163	.0218	.0028
2008:1–2009:4	8	.0130	.0216	.0419	.0096
2010:1–2014:2	18	.0130	.0159	.0199	.0017

Note: The table presents the S_2 and S_0 estimates for the Brazilian stock market from 1986 to 2014 in seven periods. The figures show evidence of eventual structural break due to financial crisis. Source: The author.

Table 6

Subsamples of firm level S_2 and S_0 estimates by listing segments

		S_2			
Subsample	**N. Obs.**	**Min.**	**Mean**	**Max.**	**Std. Dev.**
Bovespa	873	-.0194	.0054	.0306	.0072
N1	1843	-.0218	.0061	.0647	.0075
N2	92	.0005	.0115	.0301	.0053
NM	1409	-.0159	.0095	.0542	.0066
		S_0			
Subsample	N. Obs.	Min.	Mean	Max.	Std. Dev.
Bovespa	873	.0000	.0118	.0502	.0074
N1	1843	.0000	.0131	.0680	.0071
N2	92	.0055	.0160	.0447	.0061
NM	1409	.0000	.0141	.0542	.0075

Note: The table presents the S_2 and S_0 estimates for the Brazilian stock market from 1986 to 2014 in four listing segments. Source: The author.

The presence of various listing segments in the Brazilian stock market obliges the adoption of improved information disclosure methods and the protection of minority shareholders (Rabelo & Vasconcelos, 2002). The traditional segment (Bovespa) is expected to provide more asymmetric information compared to the new segment (NM). However, this hypothesis has not been confirmed. The averages of S_2 and S_0 for the traditional segment were higher than those for the NM segment.

The real estate industry presented a significantly higher (twice) average of asymmetric information (S_2), and textiles presented about half the full sample average of S_0 (Table 7).

The daily average of S_0 is quite similar for the Bovespa and NM segments (0.050 and 0.054 respectively), suggesting that negative values had a huge influence on the average of S_2. The negative values were from the period prior to 1994, as shown in Figure 1.

Table 7

Subsamples of firm level S_2 and S_0 estimates by industry

		S_2			
Subsample	**N. Obs.**	**Min.**	**Mean**	**Max.**	**Std. Dev.**
Food and Beverage	266	-.0104	.0070	.0542	.0077
Retail	293	-.0156	.0064	.0306	.0065
Real Estate	256	-.0053	.0122	.0333	.0068
Utilities	690	-.0194	.0092	.0285	.0065
Bank and Insurance	494	-.0159	.0051	.0647	.0076
Mining	260	-.0125	.0049	.0343	.0074
Other	555	-.0142	.0078	.0314	.0067
Paper	135	-.0171	.0049	.0392	.0084
Oil and Gas	228	-.0190	.0060	.0286	.0073
Chemical	138	-.0159	.0051	.0259	.0076
Steel	392	-.0218	.0058	.0252	.0072
Technology	21	.0042	.0086	.0140	.0020
Telecommunication	202	-.0152	.0074	.0379	.0072
Textiles	57	-.0079	.0050	.0225	.0067
Logistics	152	-.0100	.0089	.0301	.0066
Automobiles	78	-.0139	.0084	.0227	.0065

		S_0			
Subsample	**N. Obs.**	**Min.**	**Mean**	**Max.**	**Std. Dev.**
Food and Beverage	266	.0000	.0105	.0542	.0089
Retail	293	.0000	.0106	.0432	.0072
Real Estate	256	.0000	.0182	.0505	.0081
Utilities	690	.0000	.0158	.0611	.0067
Bank and Insurance	494	.0010	.0122	.0680	.0063
Mining	260	.0000	.0121	.0443	.0081
Other	555	.0000	.0131	.0433	.0057
Paper	135	.0007	.0107	.0463	.0068
Oil and Gas	228	.0004	.0142	.0418	.0076
Chemical	138	.0000	.0124	.0351	.0070
Steel	392	.0000	.0128	.0420	.0068
Technology	21	.0077	.0117	.0169	.0025
Telecommunication	202	.0000	.0142	.0475	.0069
Textiles	57	.0000	.0078	.0247	.0077
Logistics	152	.0000	.0127	.0447	.0076

Automobiles	78	.0000	.0124	.0350	.0073

Note: The table presents the S_2 and S_0 estimates for the Brazilian stock market from 1986 to 2014 by industry. Source: The author.

The variables representing the growth opportunity set, leverage, size, and returns have been standard in the financial literature, because they represent the characteristics that really differentiate companies (Titman & Wessels, 1988; Demirgüc-Kunt, Feyen, & Levine, 2013). The descriptive statistics of M/B, D/E, SIZE, and RETURN are shown in Table 8. Note that variable size has no observations for the second quarter of 1986 and it does not change the statistical sense or significance of the cointegration results.

Table 8

Descriptive Statistics of variables related to asymmetric information

Variable	N. Obs.	Min.	Mean	Max.	Std. Dev.
M/B	111	.0000	4.5154	108.7100	14.2290
D/E	111	.0000	0.4627	6.0384	0.7400
SIZE	110	12.5510	18.5630	21.2370	2.0885
RETURN	111	-0.4030	0.0481	0.6356	0.2175

Note: The table presents the descriptive statistics of the variables' aggregate data that could be related to asymmetric information, such as the growth opportunity set, leverage, size, and stock return for the Brazilian stock market from 1986 to 2014. Source: The author.

Cointegration analysis (Table 9) shows that asymmetric information has a long-run relationship with M/B, D/E, SIZE, and RETURN. This result is consistent with the prediction that these variables discriminate between companies. Time-varying cointegration also shows that the vectors vary in different periods.

However, the sense of relationship has to be carefully considered. From Table 9, M/B and RETURN were negatively associated to asymmetric information. RETURN would be the reason of asymmetric information, but certainly the negative relationship is due to the extent of uninformed traders facing losses from asymmetric information (Grossman & Stiglitz, 1980).

The growth opportunity set would be related to asymmetric information because it represents the younger companies, but the results show the opposite relationship. This indicates that asymmetric information is also present in more consolidated companies. This specific finding is consistent with Minardi, Sanvicente, and Monteiro (2006) owing to liquidity issues.

Table 9

Time-varying cointegration equation of asymmetric information

	S_2		**S_0**	
VECM				
M/B	-0.0022		-0.0029	
D/E	0.0821		0.1012	
SIZE	0.0045		0.0053	
RETURN	-0.0715		-0.0888	
p	1		1	
r	1		1	
#OBS	114		114	
TV VECM	LRtvc	p-value	LRtvc	p-value
m=1	3.0500	0.6924	5.2000	0.3921
m=2	11.4400	0.3239	16.7300	0.0806
m=3	17.8400	0.2709	20.8700	0.1410
m=4	43.8000	0.0016	47.1800	0.0005
m=5	70.9400	0.0000	66.4800	0.0000
m=6	87.8100	0.0000	82.6100	0.0000
m=7	91.8900	0.0000	88.6200	0.0000
m=8	100.9400	0.0000	93.4400	0.0000
m=9	107.4600	0.0000	99.0400	0.0000
m=10	113.5400	0.0000	114.9000	0.0000
m=11	119.9800	0.0000	144.1100	0.0000
m=12	130.2700	0.0000	165.2400	0.0000
m=13	170.8300	0.0000	202.1800	0.0000
m=14	245.3600	0.0000	279.1900	0.0000
m=15	302.7000	0.0000	338.4000	0.0000

Note: The table presents the time-varying cointegration equation and tests (Bierens & Martins, 2010) among S_2 and S_0 and variables representing the growth opportunity set, leverage, size, and stock returns in the Brazilian stock market from 1986 to 2014, where *p* is the number of periods of optimal choice for lagged variables, r is the number of ranks or cointegration equation, and m is the maximum number of polynomials of the Chebyshev time polynomials. Source: The author.

5 Concluding Remarks

The main implication of this paper is that the Corwin-Schultz measures are stationary, valid, and reliable. Thus, there is an easy method to compute asymmetric information in the Brazilian stock market. With a quarter in advance, one can forecast the behaviour of firm-level variables.

The subsamples of S_2 and S_0 show that industries can be more sensitive to asymmetric information, and that the average asymmetric information of the traditional segment can still be lower than that of other segments. This finding suggests a combined research between industry and segments on the real effects of different listing segments.

To test the financial and economic theories in developing markets, we need to develop S_2 and S_0 as measures of asymmetric information. For practical applications, S_2 and S_0 measures can help investment managers select stocks with higher asymmetric information as well as informed traders.

This study has some limitations. The Brazilian stock market has been changing during the last 15 years. Although the developing Brazilian market has around 500 listed companies, our sample considered only 68 companies with the most traded shares. Furthermore, we considered Corwin and Schultz's (2012a) allegation that the actual high and low prices of infrequently traded stocks were not observed. The choice of this sample is based only on the actual level of asymmetric information in the Brazilian stock market. We tried to address the Ibovespa methodological changes with some eventual adjustments, survival bias, and so on, but mainly sought a measure to represent asymmetric information for other studies.

Unit root and cointegration methods are time-series techniques. The results were compared with the asymmetric information measure standard in the literature. Therefore, researchers need to address other markets, techniques, and measures to improve the robustness of the Corwin–Schultz measures. We conjecture that the Corwin–Schultz measure would be reliable only if it were similar to the PIN score, thus allowing for generalization and replication of the study.

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