

Pricing and spread components at the Lima Stock Exchange

*Luis Chávez-Bedoya, Carlos Loaiza Álamo
and Giannio Téllez De Vettori*

ABSTRACT

This paper analyses three aspects of the share market operated by the Lima Stock Exchange: (i) the short-term relationship between the pricing, direction and volume of order flows; (ii) the components of the spread and the equilibrium point of the limit order book per share, and (iii) the pricing, order direction and trading volume dynamic resulting from shocks in the same variables when lagged. The econometric results for intraday data from 2012 show that the short-run dynamic of the most and least liquid shares in the General Index of the Lima Stock Exchange is explained by the direction of order flow, whose price impact is temporary in both cases.

KEYWORDS

Stock markets, stocks, prices, econometric models, Peru

JEL CLASSIFICATION

G11, G12, G15

AUTHORS

Luis Chávez-Bedoya teaches finance at the ESAN Graduate School of Business, Lima, Peru. lchavezbedoya@esan.edu.pe

Carlos Loaiza Álamo teaches at the Faculty of Administration and Finance of the Peruvian University of Applied Sciences (UPC), Lima, Peru. cloaizaa@pucp.pe

Giannio Téllez De Vettori is a teaching assistant at the Department of Economics of the Catholic University of Peru and a researcher affiliated with the ESAN Graduate School of Business, Lima, Peru. giannio.tellez@pucp.pe

I

Introduction

The Peruvian stock market has struggled to develop sustainably as an investment alternative, yet little basic or applied research has been done on it. There is no significant body of research dealing theoretically, empirically, or both, with the workings of this market, and specifically the share market. This lack of research was the spur for the present paper, which aims to contribute to an understanding of the pricing dynamic and the composition of order execution costs in the trading mechanism operated by the Lima Stock Exchange.

The main asset pricing models, namely Markowitz's (1952) portfolio selection model and Sharpe's (1964) capital asset pricing model, present risk and expected yield as price determinants. Trading costs are zero in both models, an assumption that is relaxed in financial market microstructure theory. This theory is the study of the process and outcomes of exchanging financial instruments under explicit trading rules (O'Hara, 1995).

There are two major obstacles to studying the empirical evidence for the microstructure theory: (i) obtaining share trading microdata, and (ii) coping with bulky information in empirical testing. It was possible to

obtain this information for the present study, however, with a view to obtaining a better understanding of the behaviour of the Lima Stock Exchange share market. In these favourable circumstances, the effects of the dynamic of pricing and the components of the bid-ask spread in the Lima Stock Exchange share market have been investigated along the lines of analyses carried out for the world's most developed stock markets. As far as we know, this is the first study to empirically test microstructure theory for the Peruvian equity market.¹

This document is organized as follows. Section II describes the trading mechanism at the Lima Stock Exchange. Section III lays out the theoretical framework representing the current state of knowledge. Section IV describes the data and the treatment applied to them, and gives the results of the econometric estimations. Lastly, section IV presents the conclusions.

¹ See Loaiza (2013) for the first theoretical presentation on microstructure for the Lima Stock Exchange.

II

The share trading mechanism at the Lima Stock Exchange

The study of microstructure requires an understanding of a stock market's trading mechanism, so these characteristics will now be described for the Peruvian stock market.

The Lima Stock Exchange has an electronic trading mechanism² which aggregates buy and sell orders in the limit order book (LOB). There are no market-makers,³ so liquidity is provided by the LOB alone. There is a price

discrimination rule, which operates at every stage of a trade and means that an order may be executed piecemeal at different prices. Here, priority (the order of execution) and allocation (the matching of supply and demand) are as follows: first, the order that "bets the price"⁴ in the LOB; second, the order with the "greatest exposure time in the market".⁵

² The trading mechanism is ELEX, a software system that aggregates buy and sell orders in the limit order book (LOB). These are automatically matched following best price and time rules in a continuous auction. Orders can also be executed at different prices.

³ Although there are regulations for agents carrying out market-making functions, in practice there are no market-makers. See Loaiza (2013).

⁴ What it means to better the price in the LOB depends on whether a buy or sell order is involved. Since the goal is to reduce spreads, a buy order better the price if it is higher than the highest bid in the LOB. Conversely, a sell order better the price if it is lower than the lowest offer in the LOB.

⁵ The provision relating to exposure time in the market means that priority is given to whoever first initiates an order.

Initial price formation occurs in a first phase known as the pre-open session, when the auction system takes non-cancellable orders. At this stage, all market expectations are stored but not matched. The system then uses this information to allot a price in a “variable time period”⁶ so that the orders can be executed.

The next phase is continuous trading, when traders enter orders in the expectation that they will be matched automatically. These are limit orders allowing securities to be bought or sold by specifying the order quantity, price and exposure period. With a limit order, it is not permitted to enter prices that fall below the minimum movement limit (tick) of 0.01 or that exceed a maximum variation of 15% for local securities and 30% for foreign securities relative to the last price cleared the day before.⁷ The trading mechanism of the Lima Stock Exchange does not permit market orders (those not executed at a limit

price). Traders can view a market by price in the book, on both the bid and ask sides. A best price is determined from the limit orders received and can be viewed in the aggregate (not individually) by traders participating in the LOB. The difference between the best bid and ask prices is the spread.

The final phase is the close, which works much like the pre-open session, with a closing price being set for shares within an arbitrary time range.⁸ Once this price has been set, any buy or sell order entered is traded at that value. Thus, each share is priced on the basis of the net aggregate demand for it (purchases minus sales) at each point in time during continuous trading. This price dynamic may be affected by problems of information asymmetry between investors and the immediacy with which their trades are executed; these problems give rise to costs that are known as “frictions” in the microstructure literature, as they affect price formation.

⁶ This means that the first trade of the day takes place in an interval of +/- 2 minutes from the start of the following stage, that of continuous trading.

⁷ For all phases of trading.

⁸ This means that the last trade in the trading phase takes place within an interval of +/- 2 minutes from the start of the following (closing) stage.

III

Microstructural models

This section reviews theoretical and empirical models based on microstructural stock market theory, which can be used to determine the best approach to explaining share trading on the Lima Stock Exchange.

1. Some models based on the stock market microstructure approach

With regard to the current state of knowledge, the work of Demsetz (1968) marks the beginning of research in the field of microstructure, analysing price-setting in share markets. This author incorporates the problem of trading immediacy owing to the existence of impatient traders requiring liquidity and patient traders without liquidity needs who come into the market at different points in the trade.

Garman (1976) was the first to model a trading process characterized by the presence of an agent managing an inventory of shares and cash. His model is characterized by temporary imbalances in flows of buy and sell orders (Demsetz, 1968), which produce uncertainty about when an order may be expected to

come in. These imbalances justify the presence of a market-maker who can resolve the problem of uncertainty regarding the time it will take for an order to come in. The market-maker solves the problem by offering shares when the counterparty is buying, and cash when the counterparty is selling.

Stoll's (1978) model also sets out from the immediacy problem and defines a market-maker as a provider of liquidity or trading services. This agent will seek to compensate for the costs of offering immediacy via the spread, paying a lower price to those wishing to sell assets and selling at a higher price to those wishing to purchase assets. In this model, Stoll breaks costs down into: (i) maintenance costs; (ii) processing costs,⁹ and (iii) information costs. However, the author focuses on the maintenance cost, assuming that the market is competitive and the other costs are zero.

⁹ Stoll (1978 and 2000) calls processing costs those related to the routing or electronic transmission of orders, execution and settlement.

Glosten and Milgrom (1985) model the problem of information asymmetry creating adverse selection costs in share trading. The model assumes the sequential arrival of traders with private information (insider traders) and those requiring liquidity (liquidity traders) in a market with perfect competition. Market-makers revise their prices against the information they extract from the order flow, using a Bayesian learning process. In this model, information is extracted from order direction rather than size. A second important study modelling the problem of information asymmetry is that of Kyle (1985), which assumes a rational expectations equilibrium, single auctions (there is no spread) and a market with imperfect competition. Thus, the informed trader acts strategically by anticipating the reactions of other agents. The outcome is that the transaction costs of the uninformed agents are equivalent to the profits of the informed agents.

Stoll (2000) divides operating costs into two classes: “real frictions” and “informational frictions.” Both classes affect price formation. In the first case, the market-maker sets out to compensate for order processing and inventory costs and to obtain rents from his market power, while in the second he is an intermediary who redistributes wealth between informed and uninformed traders, incurring adverse selection costs only. Then, Stoll (2000) attributes temporary price changes to real friction problems and permanent price changes to informational friction problems.

Hitherto, microstructure theory has centred on mechanisms where there is a market-maker. However, share trading is not always expedited by such an agent, as there is also the possibility of the LOB being the liquidity provider. The problem with LOB models is that they have only been developed theoretically (Rosu, 2009; Foucault, Kadan and Kandel, 2001); nonetheless, Glosten (1994) developed a theoretical LOB model with information asymmetry problems, where investor behaviour is modelled from a price revision equation, which can be empirically calculable and will determine the input of limit orders.

Jong, Nijman and Röell (1996) use the Glosten (1994) model to analyse the effect on intraday prices of the bid-ask spread components on the Paris Bourse. The empirical test consists of an econometric model where the spread is decomposed into two factors, one caused by order processing costs and the other by information asymmetry.

Jong, Nijman and Röell (1996) develop two estimates: in the first they use ordinary least squares (OLS) to analyse the immediate effect on prices, and in the second they use a vector autoregression (VAR) model

to analyse whether the effect on prices is permanent, applying the methodology proposed by Hasbrouck (1991a). They conclude that processing costs are higher and adverse selection costs lower in smaller operations. They also find that the effect of order direction (buying or selling) on prices in later periods is permanent.

It can be concluded from this review of the literature that the share trading mechanism may be subject to operating costs comprising processing costs and adverse selection costs. Given the trading characteristics described for the Lima Stock Exchange, the model considered to be the best fit is the one based on the LOB. One theoretical approach that has been contrasted for models of this type is that of Glosten (1994). This empirical contrast is carried out by Jong, Nijman and Röell (1996) following the econometric methodology proposed by Hasbrouck (1991a). The present study will contrast this model. Glosten’s (1994) model and its extension by Jong, Nijman and Röell (1996) will now be presented.

2. Glosten’s (1994) model and its extension by Jong, Nijman and Röell (1996)

Glosten (1994) develops a theoretical model which assumes an LOB, discriminatory pricing and no market-maker, all three of which are characteristics of the trading model at the Lima Stock Exchange. As described in section III.1, this paper models investor behaviour and equilibrium characteristics in an LOB when a great many limit orders come in. The investor decides to enter a buy order if the marginal valuation is at least as great as the asset price, and the LOB equilibrium is characterized by an expected return of zero where, in a context of strong adverse selection, the losses of some traders are the profits of informed traders. Then, Jong, Nijman and Röell (1996) extend the model by developing a calculable equation for Glosten’s (1994) theoretical model, incorporating processing costs. The derivation of the equation for the share pricing dynamic and the components of the price spread will now be presented.

In Glosten’s (1994) original model, there are no order processing costs and buyer-initiated transactions are assumed. Let $R(q)$ be the “price revision” equation, denoted by the price a buyer executes on an order of size q over and above the initially expected value of the order. In Glosten’s (1994) model, q represents the minimum level for price clearing,¹⁰ with the marginal

¹⁰ A trade must be worth at least one tax unit (UIT) to make a price at the Lima Stock Exchange; otherwise, the trade will not change the price even if executed.

value of a transaction of size q being determined by the following rule:

$$R'(q) = E_z(g(Z) | Z \geq q) \quad (1)$$

where $g(Z)$ is the revision to the best public estimate of the value of the share when it is known that the buyer will execute an order of size Z in the market. E_z denotes the expectation that arises about the distribution of the size of transaction Z . This distribution is assumed to be exponential, so that:

$$F_z(z) = 1 - e^{-\frac{z}{\alpha}} \quad (2)$$

Price revision is described as the change in expectations about the true value of the share, owing to an operation of size Z . To simplify, this relationship is assumed to be linear:

$$g(Z) = g_0 + g_1 Z \quad (3)$$

On these assumptions, the marginal price ratio is:

$$R'(q) = g_0 + g_1 E_z(Z | Z \geq q) = g_0 + g_1 (q + \alpha) \quad (4)$$

where the last equality derives from the properties of the exponential distribution, α being the average transaction size. Then, Jong, Nijman and Röell (1996) propose an extension to Glosten's (1994) model, introducing an order processing cost into the marginal pricing scheme. Let the function of the order processing cost, denoted by $C(q)$, be:

$$R'(q) = C'(q) + g_0 + g_1 (q + \alpha) \quad (5)$$

Integrating (5) and dividing by q gives the average price:

$$\int R'(q) dq = \int C'(q) dq + \int (g_0 + g_1 \alpha) dq + \int g_1 q dq \quad (6)$$

$$R(q) = C(q) + (g_0 + g_1 \alpha)q + g_1 \frac{q^2}{2} \quad (7)$$

$$\frac{R(q)}{q} = \frac{C(q)}{q} + (g_0 + g_1 \alpha) + \frac{1}{2} g_1 q \quad (8)$$

To simplify, the average order processing cost is assumed to be a quadratic function of q ,¹¹ i.e., $C(q) = c_0 q + c_1 q^2$. Thus,

$$\frac{R(q)}{q} = \frac{(c_0 q + c_1 q^2)}{q} + (g_0 + g_1 \alpha) + \frac{1}{2} g_1 q \quad (9)$$

so that

$$\frac{R(q)}{q} = c_0 + c_1 q + (g_0 + g_1 \alpha) + \frac{1}{2} g_1 q = R_0 + R_1 q \quad (10)$$

where $R_0 = c_0 + g_0 + g_1 \alpha$ and $R_1 = c_1 (1/2) g_1$. R_0 captures the determinants of the average price that are unrelated to the quantity traded, whereas R_1 captures determinants that are directly related to the transaction amount. Lastly, the following breakdown of the bid-ask spread can be derived from Glosten's (1994) model:

$$ASC = (g_0 + g_1 \alpha) + \frac{1}{2} g_1 q \quad (11)$$

$$OPC = c_0 + c_1 q \quad (12)$$

where ASC is the adverse selection cost and OPC is the order processing cost. To apply this model empirically, the following notation from Jong, Nijman and Röell (1996) is introduced:

p_t = logarithm of the purchase price (average price paid per share).

q_t = quantity (number of shares traded).

Q_t = direction of trade.¹²

y_t = expected value of the share before the trade.

ϵ_t = change in share value.

It is established in the empirical model that the transaction price is equal to the expected value of the

¹¹ It should be noted that this implies a quadratic cost function with an intercept of zero.

¹² It is important to analyse the direction of the order, since this provides information about whether the intention is to acquire or dispose of shares, affecting LOB demand (buy) or supply (sell). If the operation is initiated by a buy order, the direction of trade will have a positive sign, taking a value of +1. If the operation is initiated by a sell order, the direction of trade will have a negative sign, taking a value of -1. The direction of a buy order is assumed to be positive because greater demand will drive up the price. Conversely, the direction of a sell order is assumed to be negative because greater supply will drive down the price.

share prior to the operation plus the average price premium, $R(q)/q$, given by equation (10). As in Madhavan, Richardson and Roomans (1994), a random price error, u_t , is added to capture other influences on the transaction price, such as pricing discretion.

The term u_t is not considered to be correlated with other variables in the price equation. Additionally, pricing is assumed to be determined by order direction and flow, which are made known at a time prior to execution ($t-1$), revealing information to the market. The pricing equation thus becomes:

$$p_t = y_t + (R_0 + R_1 q_{t-1})Q_{t-1} + u_t \quad (13)$$

The price revision can be modelled by the change in the expected value y_t , as well as future trades and order direction and flow, given pricing as follows:

$$y_{t+1} = y_t + (g_0 + g_1 q_{t+1})Q_{t+1} + \epsilon_{t+1} \quad (14)$$

Equation (14) derives from equation (3), where ϵ_t is public information that is encountered between transactions t and $t+1$ but is not related to the current transaction. When equation (14) is used, we get:

$$y_{t+1} - y_t = (g_0 + g_1 q_{t+1})Q_{t+1} + \epsilon_{t+1} \quad (15)$$

$$\Delta y_{t+1} = (g_0 + g_1 q_{t+1})Q_{t+1} + \epsilon_{t+1} \quad (16)$$

And iterating one period back gives:

$$\Delta y_t = (g_0 + g_1 q_t)Q_t + \epsilon_t \quad (17)$$

Now, if equation (13) is presented in terms of variations:

$$\Delta p_t = \Delta y_t + (R_0 + R_1 \Delta q_{t-1})\Delta Q_{t-1} + \Delta u_t \quad (18)$$

Equation (17) is substituted into (18):

$$\Delta p_t = (g_0 + g_1 q_t)Q_t + \epsilon_t + (R_0 + R_1 \Delta q_{t-1})\Delta Q_{t-1} + \Delta u_t \quad (19)$$

$$\Delta p_t = (R_0 + R_1 \Delta q_{t-1})\Delta Q_{t-1} + (g_0 + g_1 q_t)Q_t + e_t \quad (20)$$

where $e_t = \epsilon_t + \Delta u_t$. Equation (20) is interpreted as follows: the coefficients of the difference variables are the intercept and the slope of the average price, while the coefficients of the levels are estimated from the intercept and the slope of the price revision function. In other words, the variations effect is the trading effect, and the levels effect is the clearing (liquidity) effect.

The equation to be estimated is obtained by reordering (20):

$$\Delta p_t = c + R_0 \Delta Q_{t-1} + R_1 \Delta(q_{t-1} Q_{t-1}) + g_0 Q_t + g_1 q_t Q_t + e_t \quad (21)$$

$$c_0 = R_0 - g_0 - g_1 \alpha \quad (22)$$

$$c_1 = R_1 - (1/2)g_1 \quad (23)$$

Equation (21) is the equation for the pricing dynamic; the constant c is included in this equation to capture average returns across transactions (i.e., a non-zero average of e_t). Equations (22)¹³ and (23) are the determinants of order processing costs.

¹³ α is the average transaction size divided by 2.

IV

Empirical testing

1. The data

Model estimation will be carried out using Lima Stock Exchange intraday (operation by operation) electronic trading data for 2012. The assets chosen for analysis are the five most liquid shares¹⁴ and the five least liquid shares¹⁵ in the General Index of the Lima Stock Exchange (IGBVL).¹⁶

The variables worked with are:

- (i) Price variation (Δp_t): this is the differential of the logarithm of the purchase price relative to the previous price.
- (ii) Direction of trade (Q_t): the operation will have a positive sign (+1) if initiated via a buy order and a negative sign (-1) if initiated via a sell order.
- (iii) Pricing index (q_t_index): the index created is

$$q_t_index = \text{Ln} \left(\frac{\text{transaction amount}_t}{1UIT} \right)$$

where the transaction amount is the order clearing price multiplied by the quantity traded:

$$\text{Transaction amount}_t = P_t * \text{number of shares traded}$$

Transaction size is normalized, since actual transaction amounts are too volatile and estimates are affected by information disclosure issues. This is why it is necessary to ascertain whether the actual transaction amount is enough to make a price or not,¹⁷ this being the benchmark for positions and strategies in trading operations.

2. Econometric treatment

The econometric treatment applied in this study encompasses two methodologies, a Newey and West (1987) OLS model and a VAR model. With regard to the first methodology, Harris (1986) and Hasbrouck (1991a) argue that observed covariance patterns in transaction returns are more consistent with transaction time than with “calendar” time; it is therefore inferred that the relevant “clock” is transaction time. Since variations can depend on the time of day, trade size and other factors, errors are likely to be heteroskedastic. Again, if equation (21) is inaccurate, the regression error will have a series MA(1) correlation pattern.¹⁸ With this error structure, the OLS model provides consistent point estimates; however, the usual standard error formula is incorrect. For this reason, the Newey and West (1987) methodology is used so that estimation of the parameters is consistent and the variance is properly estimated.

The model presented could have two disadvantages, however. First, the estimates assume a correct model specification. For example, it is assumed that all asymmetrical information is revealed immediately after the transaction, so that there is only an immediate effect on trading prices and there are no delayed effects. Secondly, the trading pattern is assumed to be exogenous.¹⁹ If this pattern were not exogenous, the regression coefficients could be skewed because some relevant lagged variables could be omitted.

In the light of these considerations, we estimate a VAR model introduced into the market microstructure literature by Hasbrouck (1991a and 1993), which takes account of the problems mentioned in the previous paragraph. In the VAR, the clearing price and the trading dynamic are modelled using the following system of equations:

$$\begin{pmatrix} 1 & -b_0 \\ 0 & I \end{pmatrix} \begin{pmatrix} \Delta p_t \\ x_t \end{pmatrix} = \begin{pmatrix} a(L) & b(L) \\ c(L) & d(L) \end{pmatrix} \begin{pmatrix} \Delta p_{t-i} \\ x_{t-i} \end{pmatrix} + \begin{pmatrix} u_{1t} \\ u_{2t} \end{pmatrix}, \quad (24)$$

$$V \begin{pmatrix} e_{1t} \\ e_{2t} \end{pmatrix} = \begin{pmatrix} \sigma^2 & 0 \\ 0 & \Omega \end{pmatrix}$$

¹⁴ Volcan “B” (VOLCABC1), Rio Alto Mining (RIO), Ferreycorp (FERREYC1), Cerro Verde (CVERDEC1) and ADR Buenaventura (BVN).

¹⁵ Austral Group (AUSTRAC1), El Brocal (BROCALC1), Empresa Agroindustrial Pomalca (POMALCC1), Edelnor (EDELNOC1) and Scotiabank (SCOTIAC1).

¹⁶ The IGBVL comprises shares representing 80% of total liquidity in the Peruvian stock market. The reference portfolio was established in the second half of 2012.

¹⁷ For a stock price to be made in the Peruvian share market, the amount of an individual trade must be at least one tax unit (UIT), equivalent in 2012 to 3,650 nuevos soles. If this sum is not reached, the price will not change and the previous market price will continue to apply.

¹⁸ See Jong, Nijman and Röell (1996).

¹⁹ In other words, the explanatory variables do not depend on other variables (other than themselves) or on lags.

where Δp_t is the price variation and x_t is the vector of explanatory variables, with $a(L)$, $b(L)$, $c(L)$ and $d(L)$ being polynomials in the lag operator. In the present analysis, the vector of explanatory variables is the order direction (Q_t) and the size of the order flow for clearing ($Z_t = Q_t q_t$), assuming that the error terms are not correlated. This model can thus be used to analyse a dependency in the price variation, order direction and order flow size relative to past operations, without assuming that the order clearing pattern is exogenous.²⁰

To analyse the shocks of the errors (e_1, e_2) on future returns (p) and on the exogenous variables $x_t = (Q_t, Z_t)$, we need to gauge the expected value of the price τ periods after the shock, given that the system has converged on a stationary state.²¹

$$E(p_{t+\tau} - y_t | e_{1t} = 1, e_{2t} = 0, \Delta p_{t-1} = 0, \dots, x_{t-1} = 0, \dots) \quad (25)$$

$$E(p_{t+\tau} - y_t | e_{1t} = 0, e_{2t} = 0, \Delta p_{t-1} = 0, \dots, x_{t-1} = 0, \dots) \quad (26)$$

Sims (1980) popularized the idea of calculating these price effects using the impulse-response functions of a VAR model, which can be calculated by inverting the VAR to the following vector moving average (VMA):

$$\begin{pmatrix} \Delta p_t \\ x_t \end{pmatrix} = \begin{pmatrix} \alpha(L) & \beta(L) \\ \gamma(L) & \delta(L) \end{pmatrix} \begin{pmatrix} e_{1t} \\ e_{2t} \end{pmatrix} \quad (27)$$

where $\alpha(L)$, $\beta(L)$, $\gamma(L)$ and $\delta(L)$ are the moving averages of the variables mentioned earlier. Lastly, specifying the VAR model using the microstructural approach yields the following system of equations:

$$\Delta p_t = \sum_{k=0}^{\infty} \alpha_k e_{1,t-k} + \sum_{k=0}^{\infty} \beta_k e_{2,t-k} \quad (28)$$

²⁰ This assumption was made in Glosten and Harris (1988); Harris (1986); Hasbrouck (1988), and Stoll (1989).

²¹ This equation is for the case where x_t and e_{2t} are scalar. In the case of a multidimensional trading vector, the impulse responses must be calculated from a VAR model with orthogonal innovations. In this study, that is obtained by adding the variable Q_t as an explanatory variable in the size equation Z_t to obtain the orthogonal errors.

$$\Delta x_t = \sum_{k=0}^{\infty} \gamma_k e_{1,t-k} + \sum_{k=0}^{\infty} \delta_k e_{2,t-k} \quad (29)$$

It can be noted, for example, that the price differences in (28) are infinite sums of shocks in future returns and in exogenous variables. In that equation, too, the effect of the price and innovations in the trading variables (Q_t and Z_t) on the price is measured by the impulse responses α_k and β_k , respectively. Consequently, the effects of a shock on the price level (τ periods ahead) are measured by the partial sums of the impulse responses:

$$p e_1(\tau) = \sum_{k=0}^{\tau} \alpha_k \quad \text{y} \quad p e_2(\tau) = \sum_{k=0}^{\tau} \beta_k \quad (30)$$

The long-run effects of shocks would be the limits of the partial sums of $\tau \rightarrow \infty$:

$$\begin{aligned} p e_1(\infty) &= \sum_{k=0}^{\infty} \alpha_k = \alpha(1) \quad \text{and} \\ p e_2(\infty) &= \sum_{k=0}^{\infty} \beta_k = \beta(1) \end{aligned} \quad (31)$$

Given this, if the impulse responses given by the shocks dissipate over time, it can be inferred that illiquidity shocks are merely temporary. Conversely, if they do not dissipate, the conclusion is that they are permanent and have an effect in the long run. Cochrane (1988) notes that this definition of the long-run effects of innovations is unique and independent of any particular decomposition of the price process into permanent and transitory parts.

Lastly, using sign for order direction in a simultaneous dynamic model creates some problems for the estimation and computation of dynamic effects. Because Q_t is a limited dependent variable that can only take the values -1 and +1, the first VAR equation cannot be a conditional expectation of Q_t for all values of $\Delta p_{t-i} \in \mathbb{R}$ unless the coefficients of Δp_{t-i} are zero. For moderate values of Δp_{t-i} , however, the linear equation may be a good approximation to the true conditional expectation.²² Consequently, the use of Q_t as an explanatory variable in the equation Δp_t does not cause problems, since the errors of the returns equation and the other equations of the VAR are not correlated.²³ It is proposed that five

²² See Jong, Nijman and Röell (1996).

²³ See Heckman (1978).

lags²⁴ in the VAR are enough, given the general lack of residual serial correlation in the equations estimated and the fact that the standard errors are consistent estimates of heteroskedasticity.

3. Estimation results

The first equation estimated is (21), which represents the price dynamic and is presented again in this section to facilitate reading of the results.

$$\Delta p_t = c + R_0 \Delta Q_{t-1} + R_1 \Delta(q_{t-1} Q_{t-1}) + g_0 Q_t + g_1 q_t Q_t e_t \quad (32)$$

The hypothesis contrasted is that the price variation depends on order direction (Q_t) and volume traded (q_t). The results are presented in two tables: table 1 shows the results for the five most liquid shares in the IGBVL, table 2 for the five least liquid. Table 1 shows that the order direction coefficients R_0 and g_0 have positive and negative signs, respectively, for the five most liquid shares. However, R_1 and g_1 (due to RIO and CVERDEC1) do not meet the condition of always having a negative and positive sign, respectively. The regression for the Cerro Verde stock differs only in the sign of the R_1 parameter and that for the Rio Alto stock in the sign of the g_1 parameter. The five regressions in table 2 present coefficients with the same signs as are expressed in the table 1 results, with no exceptions.

Table 1 shows the coefficients estimated for the Jong, Nijman and Röell (1996) model via equation (21), the price variations being expressed in hundredths of a

percentage point, and the quantities denominated in the pricing index (q_t index). The securities chosen are the five most liquid shares in the IGBVL in 2012. Likewise, α is estimated from the median of the q_t index distribution, divided by 2, and p is the first-order error autocorrelation coefficient. The p -values, corrected by the Newey-West methodology, are shown in square brackets.

Table 2 shows the coefficients estimated for the Jong, Nijman and Röell (1996) model via equation (21), measuring price variations in hundredths of a percentage point, and using the pricing index (q_t index) as a proxy for the number of shares traded. The securities chosen are the five least liquid shares in the IGBVL in 2012, with α being estimated as the median of the q_t index distribution divided by 2, and p being the first-order error autocorrelation coefficient. The p -values, corrected by the Newey-West methodology, are shown in square brackets.

The positive sign of R_0 means that the market enters consecutive orders of the same direction and this determines whether the variation is positive or negative; if the operation is initiated as a buy order, it will tend to “better” the price²⁵ (since there will begin to be more buy orders in the LOB and demand will increase); conversely, if it is initiated as a sell order, it will tend to reduce it (since there will begin to be more sell orders in the LOB and supply will increase). The negative sign of R_1 is interpreted as the counterparty position that closes the operation. Here, it should be recalled that the model is

²⁴ See Hasbrouck (1991b).

²⁵ What it means for a price to be “bettered” depends on who initiates the trade. If it is a buyer, the price is bettered if the variation is positive. If it is a seller, the price is bettered if the variation is negative. In both cases, the price is bettered because offer limits are forced up or down (depending on whether the trade is initiated as a buy or sell operation), narrowing the spread.

TABLE 1

Estimated price coefficients for the five most liquid shares in the IGBVL, 2012

Security	Stock symbol	R_0	R_1	g_0	g_1	α	ρ	C_0	C_1
Volcan “B”	VOLCABC1	2.074 [0.000]	-0.281 [0.000]	-5.434 [0.000]	0.666 [0.000]	0.732	-0.046	7.020	-0.614
Rio Alto Mining	RIO	1.597 [0.000]	-0.044 [0.757]	-7.400 [0.000]	-0.372 [0.019]	0.686	-0.172	9.252	0.142
Ferreycorp	FERREYC1	1.749 [0.000]	-0.108 [0.426]	-6.901 [0.000]	0.558 [0.001]	0.716	-0.051	8.250	-0.387
Cerro Verde	CVERDEC1	0.809 [0.113]	0.025 [0.928]	-5.792 [0.000]	0.524 [0.013]	0.973	-0.072	6.091	-0.238
ADR Buenaventura	BVN	1.246 [0.354]	-0.765 [0.096]	-15.832 [0.000]	3.408 [0.000]	0.868	-0.234	14.119	-2.469

Source: prepared by the authors.

TABLE 2

Estimated price coefficients for the five least liquid shares in the IGBVL, 2012

Security	Stock symbol	R_0	R_1	g_0	g_1	α	ρ	C_0	C_1
Austral Group	AUSTRAC1	27.760 [0.000]	-4.687 [0.000]	-48.051 [0.000]	8.887 [0.000]	0.474	-0.180	71.602	-9.131
El Brocal	BROCALC1	2.789 [0.017]	-0.357 [0.524]	-10.243 [0.000]	0.109 [0.900]	0.492	-0.060	12.978	-0.411
Empresa Agroindustrial Pomalca	POMALCC1	13.416 [0.000]	-0.930 [0.666]	-42.864 [0.000]	4.989 [0.054]	0.075	-0.235	55.905	-3.425
EDELNOR	EDELNOC1	1.257 [0.359]	-0.521 [0.490]	-7.083 [0.000]	0.960 [0.200]	0.810	-0.225	7.562	-1.001
Scotiabank	SCOTIAC1	6.836 [0.025]	-2.750 [0.010]	-16.164 [0.000]	4.613 [0.002]	0.546	-0.372	20.482	-5.056

Source: prepared by the authors.

formulated from the buyer's side; this being so, an order can only be executed if there is a counterparty operation, so that if an investor issues a buy order (positive sign), this must be set against a sell order (negative sign). The g_0 and g_1 coefficients are interpreted with the same logic as the "variations" coefficients, with the sole difference that the former capture the dynamic of past trades, while the levels coefficients reflect the cost of the current trade.

As regards the size of the coefficients estimated, it can be seen in both tables that the order direction coefficients (R_0 and g_0) are greater than the share volume coefficients (R_1 and g_1). However, it can also be seen that the most liquid shares (table 1), on average, have order direction and share volume coefficients that are larger in absolute terms than the coefficients for the least liquid shares (table 2). The natural interpretation of this difference is that variations in the prices of the least liquid shares are more sensitive to order direction and share volume.

Tables 3 and 4 give the composition of the cost to investors of executing an order, according to Glosten's (1994) model as extended by Jong, Nijman and Röell (1996). This cost comprises the adverse selection cost, calculated from equation (11), and processing costs, calculated from equation (12), with quantities being denominated relative to the pricing index (q_t -index). For example, in the case of the most liquid share in the IGBVL, VOLCABC1, the minimum share purchase required to generate positive returns would be 6,224 shares, and the operation would generate a total cost of 18,671 nuevos soles, this being the transaction amount, i.e., the share price multiplied by the number of shares traded. Of this cost, 57.76% would be the order processing cost (10,784 nuevos soles) and 42.24% the adverse selection cost (7,887 nuevos soles). When it comes to the least liquid share in the IGBVL, SCOTIAC1, the minimum purchase of

shares in the firm required to generate positive returns would be 595. This purchase would generate a total cost of 22,905 nuevos soles, with 54.40% of this being the order processing cost (12,460 nuevos soles) and 45.60% the adverse selection cost (10,445 nuevos soles).

Both these costs are greater in absolute terms for the least liquid shares than for the most liquid ones, so that the optimum share trading volume required to obtain returns of zero is greater for the least liquid shares. As regards the proportion of each cost to the total cost, the processing cost portion is greater than the adverse selection cost portion for both the most liquid and the least liquid shares.

Table 3 shows the point at which returns become positive (zero and above) in market trading in 2012, depending on share type. The securities chosen are the five most liquid shares in the IGBVL in 2012. The median of the natural price logarithm is the reference value used to work out the number of shares traded from the transaction amount.

Table 4 shows the point at which returns become positive (zero and above) in market trading in 2012, depending on share type, with quantities being denominated relative to the pricing index (q_t -index). The securities chosen are the five least liquid shares in the IGBVL in 2012. The median of the natural price logarithm is the reference price used to work out the number of shares traded from the transaction amount.

Processing and adverse selection costs change depending on whether the share trading volume index value rises or falls. This exercise has been repeated for the other eight shares and can be found in annex A. The case of two shares, VOLCABC1 (figure 1) and POMALCC1 (figure 2), will now be shown, illustrating the differences in behaviour between a share from the most liquid group and one from the least liquid group. It

TABLE 3

Cost composition of order fulfilment for the five most liquid shares in the IGBVL, 2012

	VOLCABC1	RIO	FERREYC1	CVERDEC1	BVN
\hat{q}_t -index	1.6186	1.5290	1.5783	0.8290	0.7059
Transaction amount (nuevos soles)	18 671	17 070	17 933	8 476	7 495
Number of shares traded	6 224	3 924	7 599	215	192
Processing cost (normalized)	6.02	9.47	7.64	5.89	12.38
(in terms of \hat{q}_t -index, and absolutely)	57.76%	54.39%	55.76%	53.78%	51.47%
Adverse selection cost	4.41	7.94	6.06	5.06	11.67
(in terms of \hat{q}_t -index, and absolutely)	42.24%	45.61%	44.24%	46.22%	48.53%

Source: prepared by the authors.

TABLE 4

Cost composition of order fulfilment for the five least liquid shares in the IGBVL, 2012

	AUSTRAC1	BROCALC1	POMALCC1	EDELNOC1	SCOTIAC1
\hat{q}_t -index	4.8810	2.0560	6.9510	0.8266	1.8230
Transaction amount (nuevos soles)	487 539	28 916	3 863 510	8 457	2 905
Number of shares traded	1 875 151	629	7 289 639	2 135	595
Processing cost (normalized)	27.03	12.13	32.10	6.73	11.26
(in terms of \hat{q}_t -index, and absolutely)	54.96%	54.63%	56.07%	53.27%	54.40%
Adverse selection cost	22.15	10.08	25.15	5.91	9.44
(in terms of \hat{q}_t -index, and absolutely)	45.04%	45.37%	43.93%	46.73%	45.60%

Source: prepared by the authors.

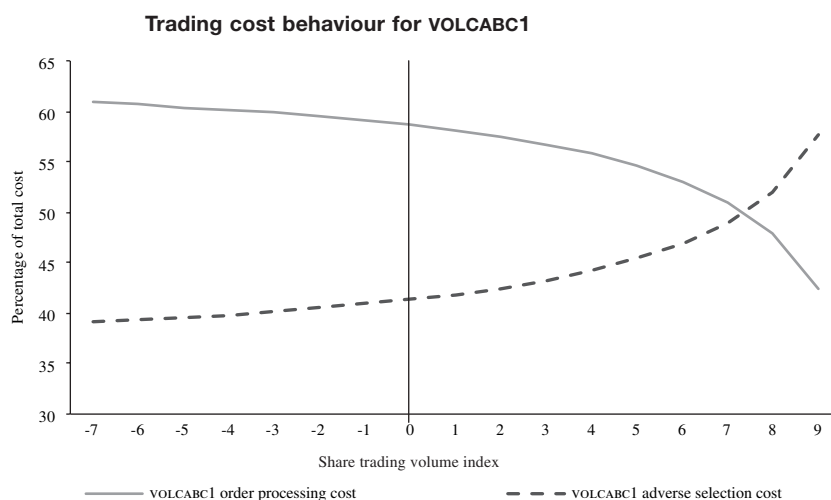
may be noted that in the case of VOLCABC1, processing costs fall in relative terms and adverse selection costs rise, a very different outcome from that seen with POMALCC1, where the proportion of each cost remains practically unchanged.

Figure 1 shows the behaviour of the cost components for VOLCABC1, which belongs to the group of the most liquid shares in the IGBVL. It can be seen that as the share

trading volume index value rises, the processing cost falls and the adverse selection cost consequently increases.

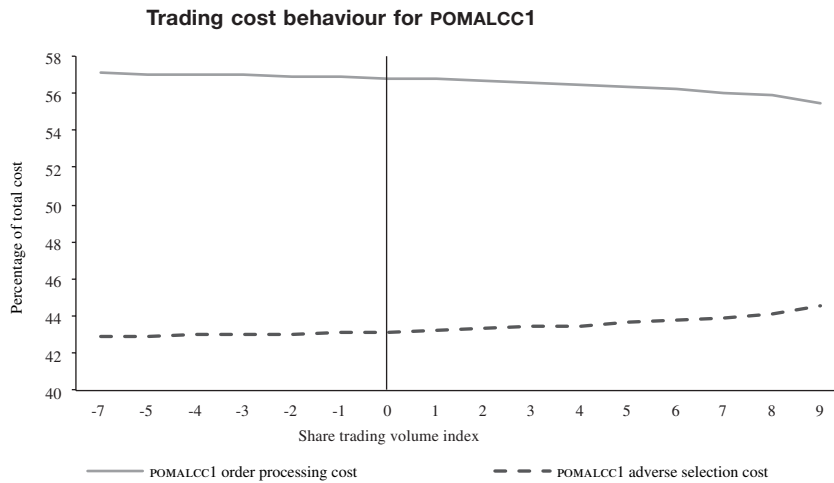
Figure 2 shows the behaviour of the cost components for POMALCC1, which belongs to the group of the least liquid shares in the IGBVL. It can be seen that as the share trading volume index value rises, the processing cost falls very slightly, so that the adverse selection cost increases slowly.

FIGURE 1



Source: prepared by the authors.

FIGURE 2



Source: prepared by the authors.

With regard to the spread components, the theoretical model predicts that when transaction amounts rise, the order processing cost will fall and the adverse selection cost increase. This behaviour is expected because when transactions involve sums which are too small to make a price and which in terms of the q_t -index are $]-\infty, 0[$, they do not affect the market or future positions in market expectations, so that the most substantial cost is the intrinsic cost of trading (the processing cost). When larger sums are transacted, conversely, the information becomes relevant and transaction amounts are indicators that provide information about positions in the asset. In this situation, investors will wish to take a position or set a price, since significant positions within a portfolio create a high level of portfolio exposure to changes in the prices concerned.

The effect of order direction and volume on price variation can be assessed in the periods following the effect at time t , with a view to analysing its continuing influence on trades thereafter. The results show that the residual price effect is less for the most liquid shares group than for the least liquid shares group. This analysis can be found in annex B. Figure 3 below presents the analysis for VOLCABC1 and figure 4 that for POMALCC1, illustrating the finding set out above.

Figures 3 and 4 shows the results of the VAR model in respect of the price dynamic ($\Delta p_t = D_{PTSHARE}$, where SHARE takes the name of the share concerned), order

direction ($Q_t = \text{SIGN}$) and the size of the order flow for clearing ($q_t, Q_t = \text{SIGN_QT_INDEX}$). It will be seen that shocks in the variables are corrected for all the shares analysed. Although the shares all evince different impulse magnitudes, it will be seen that the more liquid a share is, the faster the market correction.

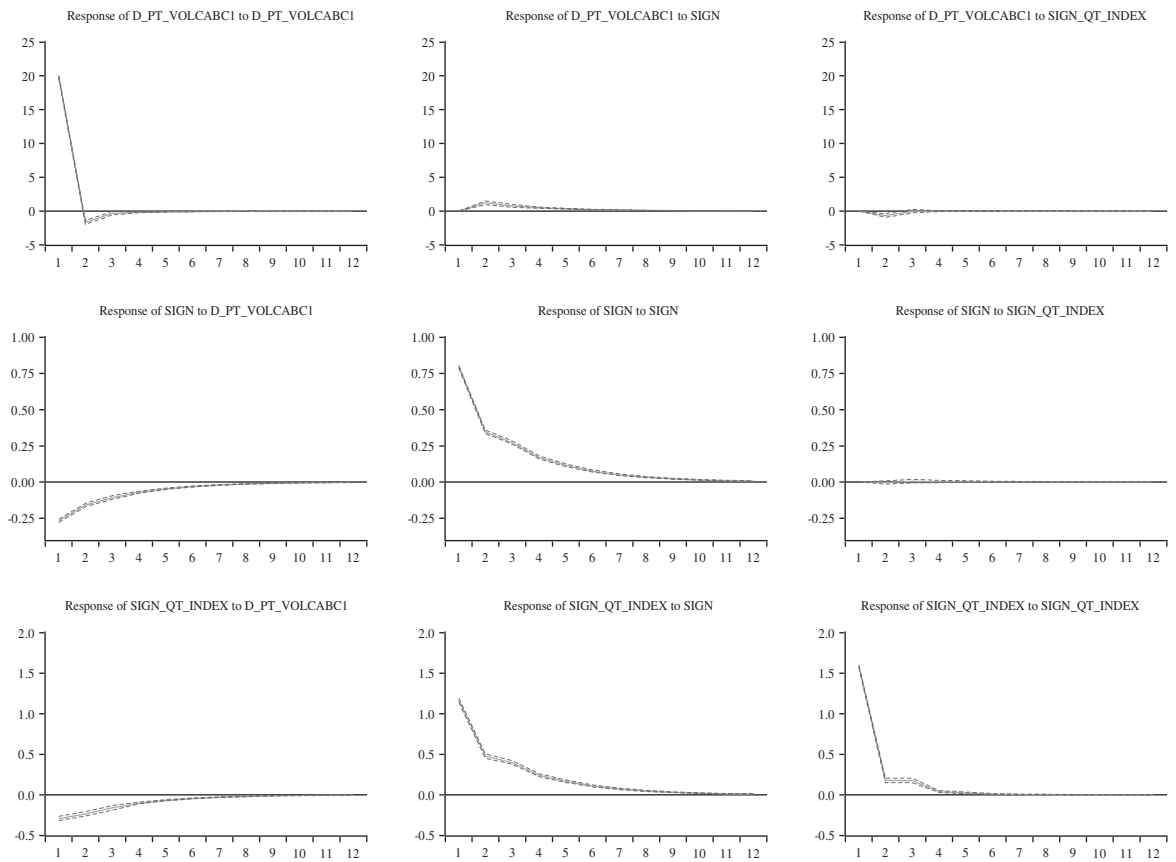
Regarding the analysis of the dynamic of order direction and transaction amount before a shock, on average the market enters orders with the same direction and then corrects. Where the variation is positive (negative), impatient agents enter buy (sell) orders in the expectation that the security will carry on rising (falling). The market will settle, i.e., the shock will be diluted, when sellers (buyers) take advantage of this rush (drop) to run down (build up) their positions, probably in order to take profits on day-trading operations.²⁶ This is why, depending on the state of liquidity of an asset, an indicator of whether the market is drying up²⁷ or not, the counterparty will “close” or trade on the best bid or ask, the level of the spread and the depth of the LOB being critical here.

²⁶ Day-trading means buying cheaply at the start of trading and selling the same shares at a higher price at the close for a profit.

²⁷ For the market to “dry up” means that the demand for or supply of an asset begins to decline, so that traders are unable to find matching orders on which to complete the operation.

FIGURE 3

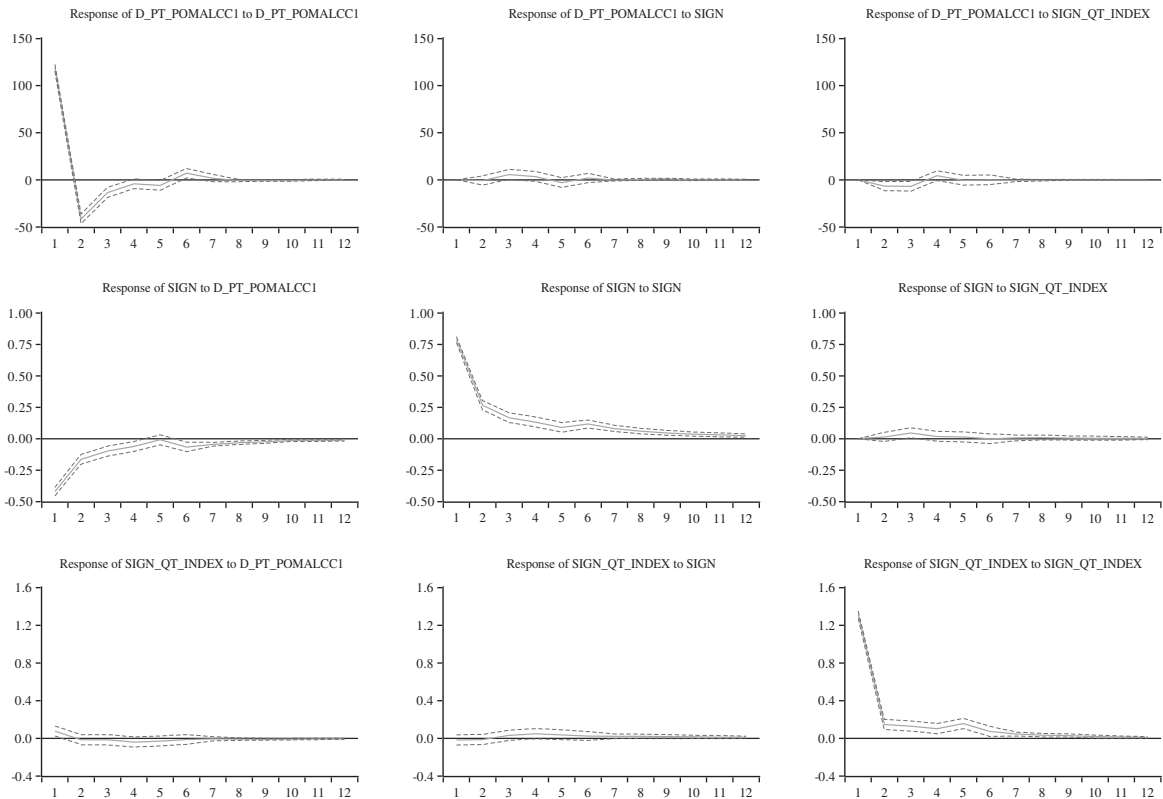
Impulse-response functions of the VAR econometric model for VOLCABC1



Source: prepared by the authors.

FIGURE 4

Impulse-response functions of the VAR conometric model for POMALCC1



Source: prepared by the authors.

V

Conclusions

The empirical results obtained by applying the Newey and West (1987) methodology show that pricing on the Lima Stock Exchange depends on the direction and number or volume of shares traded. The most important effect on the price is order direction. The group of least liquid shares presents greater sensitivity to these exogenous variables than the most liquid group. Then, the results obtained with the VAR methodology in the analysis of the price effect in subsequent periods reveal that this effect is present in a greater number of periods for the least liquid shares, meaning that, in Black's (1971) terms, they are less resilient.

Regarding the costs of executing an operation (the costs incurred by an investor to operate on the Lima Stock Exchange), the findings from the parameters estimated using the Newey and West (1987) methodology are that these costs are highest when trades are executed with the least liquid shares. Again, adverse selection costs (resulting from information asymmetry on the Lima Stock Exchange) can be interpreted as a better use of the new information that reaches the market (Stoll, 2000) via specialized investors, who obtain returns at the expense of non-specialized investors, i.e., those who do not use the new information in a correct and timely fashion.

Processing costs dominate the composition of these costs with an approximate share of 55%, the difference (45%) being made up by adverse selection costs. This cost composition changes at higher share trading volumes. For the most liquid share on the Lima Stock Exchange, VOLCABC1, adverse selection costs begin to account for a greater proportion. The situation is very different in the case of POMALCC1, with the composition remaining unchanged. Annex A shows that, generally speaking, the results are very different for each share.

The consequence for share prices of these processing and adverse selection costs is that they alter price distribution functions, enlarging or reducing distribution tails. Higher costs result in functions with fatter tails, and consequently larger spreads. Thus, the least

liquid shares present larger spreads than the most liquid shares.

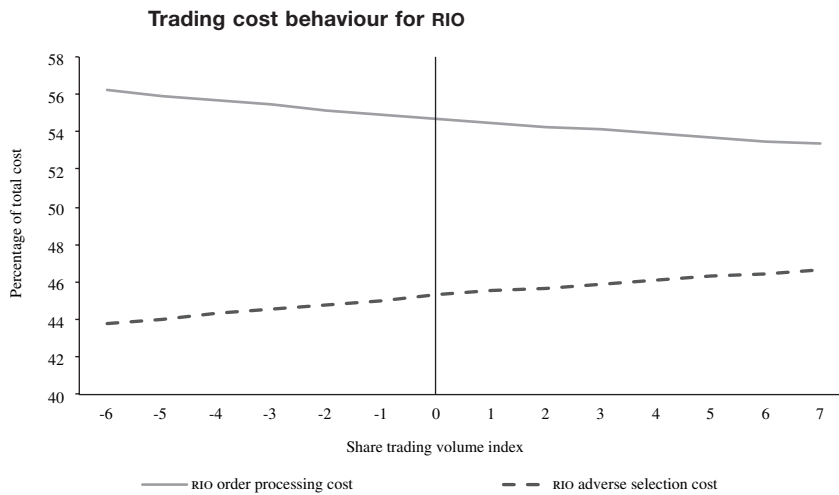
Lastly, parameters estimated by the Newey and West (1987) methodology were used to conduct an additional analysis for the calculation of the minimum number of shares needing to be traded to dilute processing and adverse selection costs. The least liquid shares have to be traded in larger numbers to dilute the costs defined in the theory presented here. It can be inferred from this finding that creating efficient portfolios with less liquid shares calls for more liquidity (cash), since a greater number of shares have to be traded for the equilibrium point to be reached. This situation could be contributing to the low liquidity presented by the share market of the Lima Stock Exchange.

ANNEX A

Figure A.1 shows the behaviour of the cost components for RIO shares. As the share trading volume index rises,

the processing cost drops very slightly, so that the adverse selection cost increases slowly.

FIGURE A.1

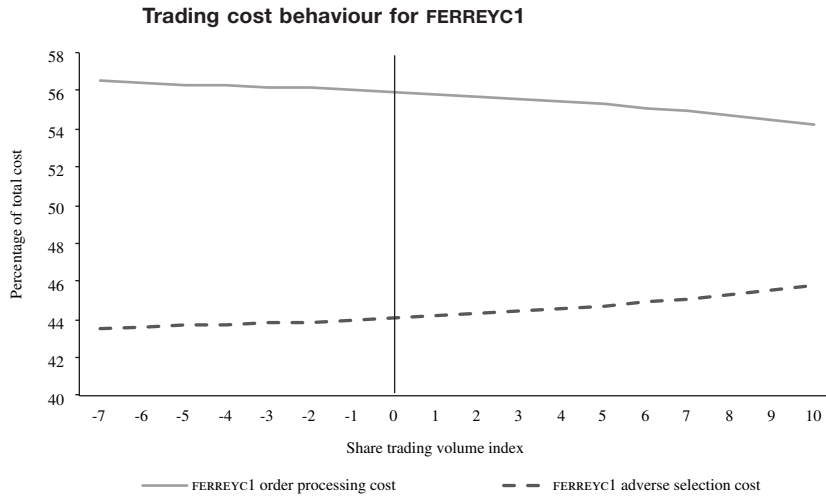


Source: prepared by the authors.

Figure A.2 shows the behaviour of the cost components for FERREYC1 shares. As the share trading volume index rises, the processing cost drops very slightly, so that the adverse selection cost increases slowly.

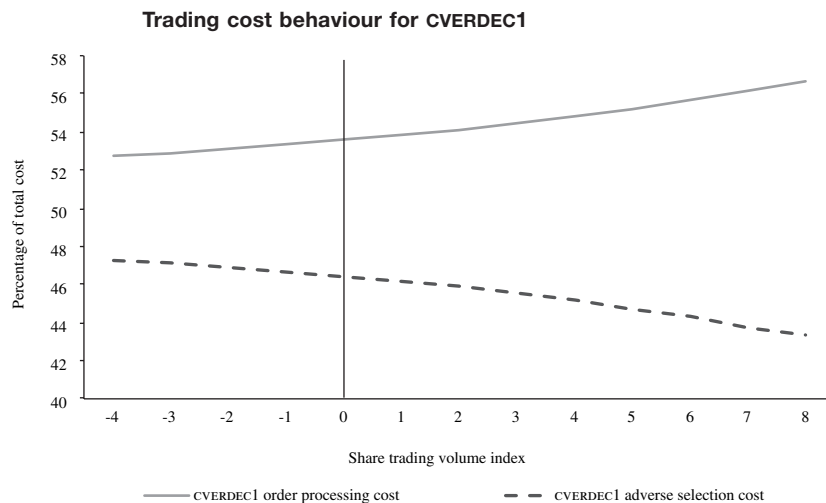
Figure A.3 shows the behaviour of the cost components for CVERDEC1 shares. As the share trading volume index rises, the processing cost increases very slightly, so that the adverse selection cost declines.

FIGURE A.2



Source: prepared by the authors.

FIGURE A.3



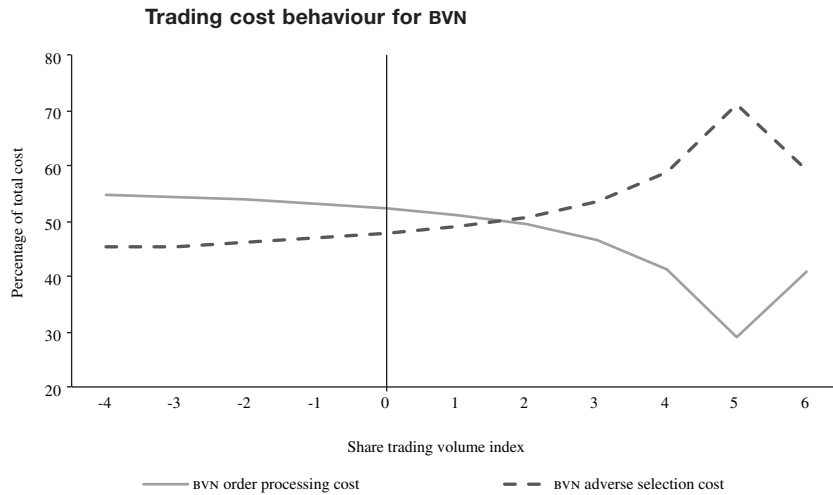
Source: prepared by the authors.

Figure A.4 shows the behaviour of the cost components for BVN shares. As the share trading volume index rises, the processing cost drops quickly, so that the adverse selection cost increases. An odd feature is that the trend is reversed once a certain level is reached, and it would be interesting

to model these components using a non-linear methodology.

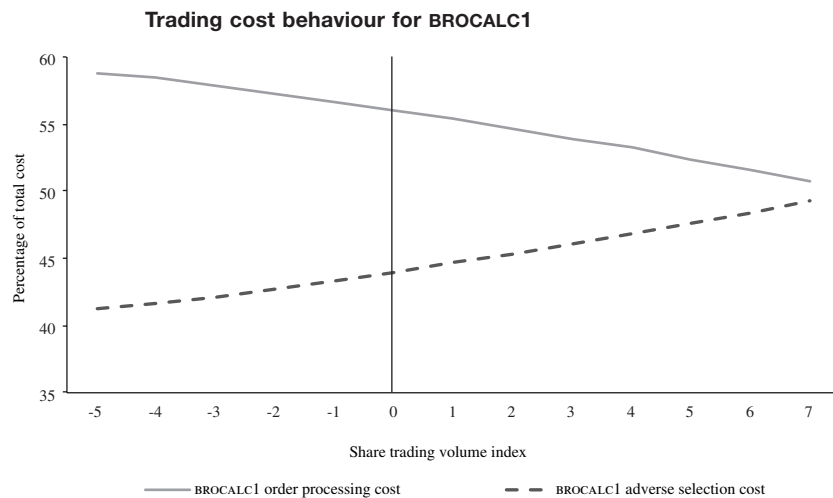
Figure A.5 shows the behaviour of the cost components for BROCALC1 shares. As the share trading volume index rises, the processing cost drops quickly, so that the adverse selection cost increases.

FIGURE A.4



Source: prepared by the authors.

FIGURE A.5

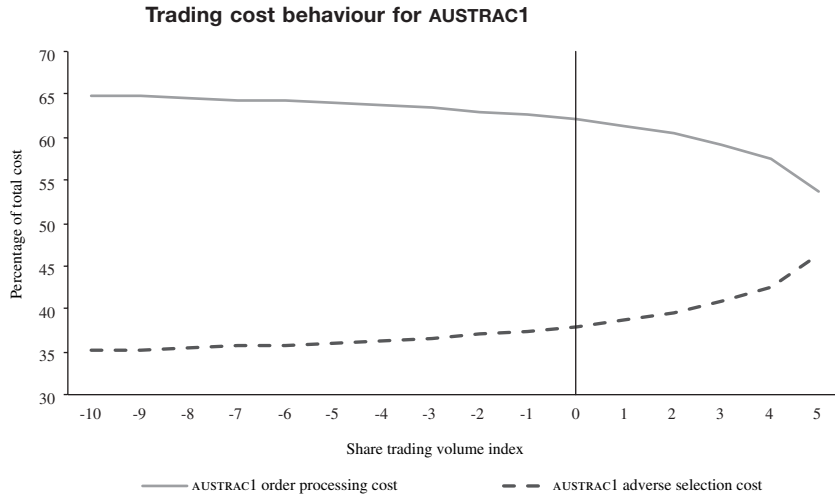


Source: prepared by the authors.

Figure A.6 shows the behaviour of the cost components for AUSTRAC1 shares. As the share trading volume index rises, the processing cost drops, so that the adverse selection cost increases slowly.

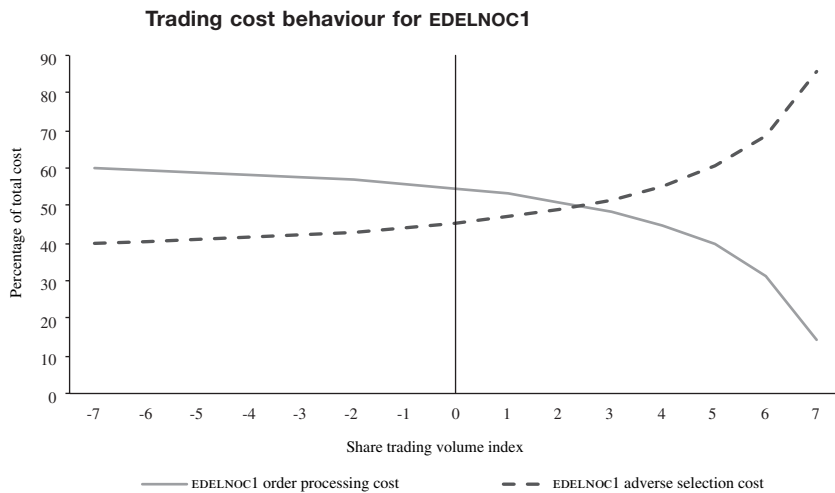
Figure A.7 shows the behaviour of the cost components for EDELNOC1 shares. As the share trading volume index rises, the processing cost drops quickly, so that the adverse selection cost increases.

FIGURE A.6



Source: prepared by the authors.

FIGURE A.7

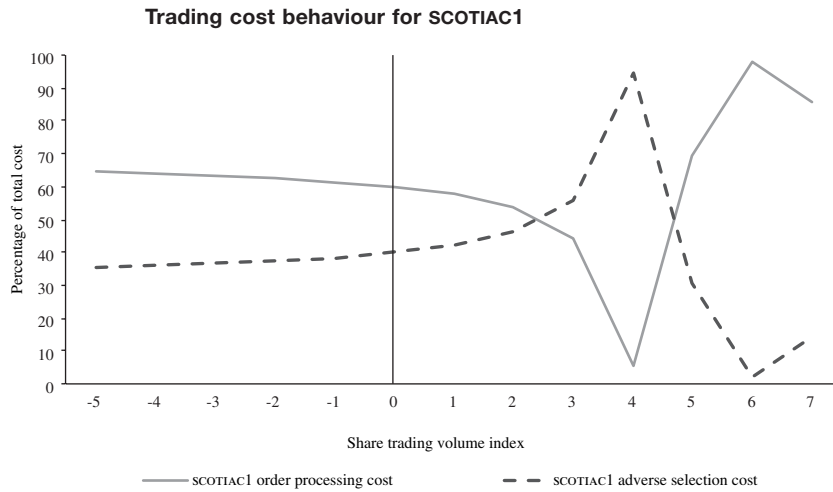


Source: prepared by the authors.

Figure A.8 shows the behaviour of the cost components for SCOTIAC1 shares. As the share trading volume index rises, the processing cost drops quickly, so that the adverse selection cost increases. An odd

feature is that the trend is reversed once a certain level is reached, and it would be interesting to model these components using a non-linear methodology, as two possible turning points can be identified.

FIGURE A.8

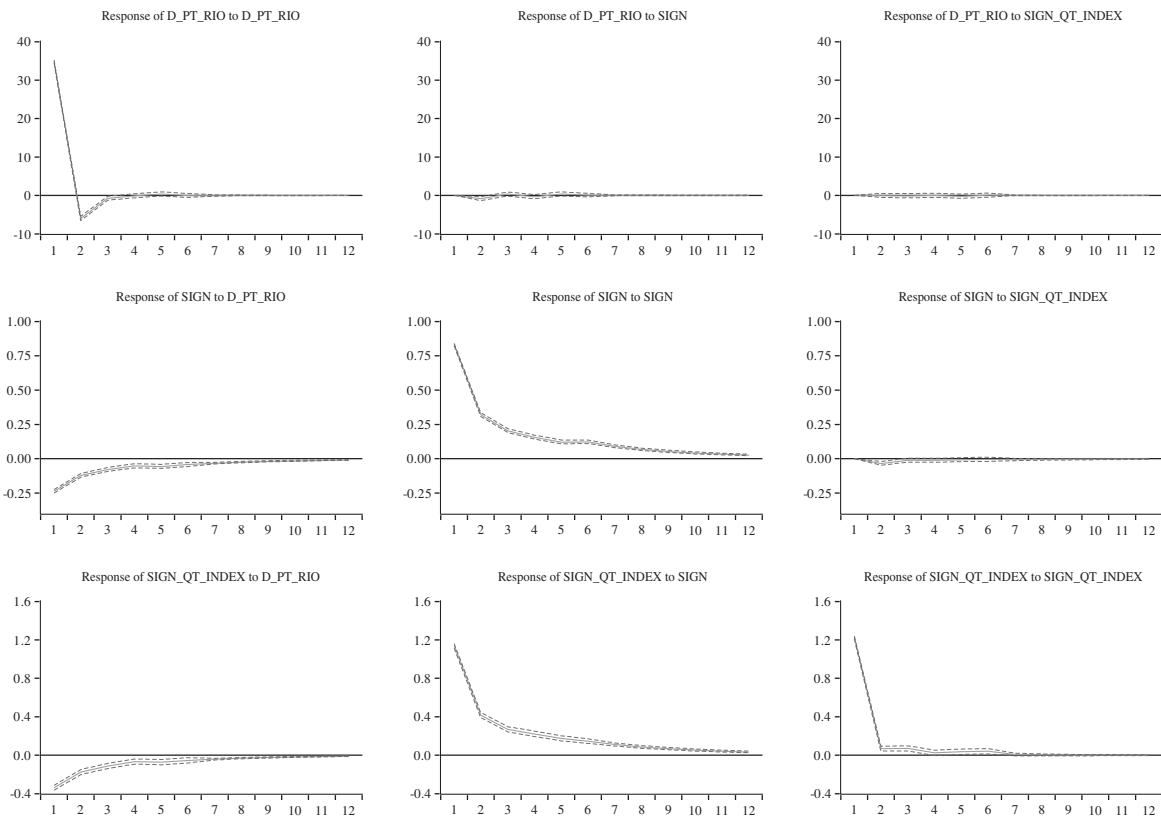


Source: prepared by the authors.

ANNEX B

FIGURE B.1

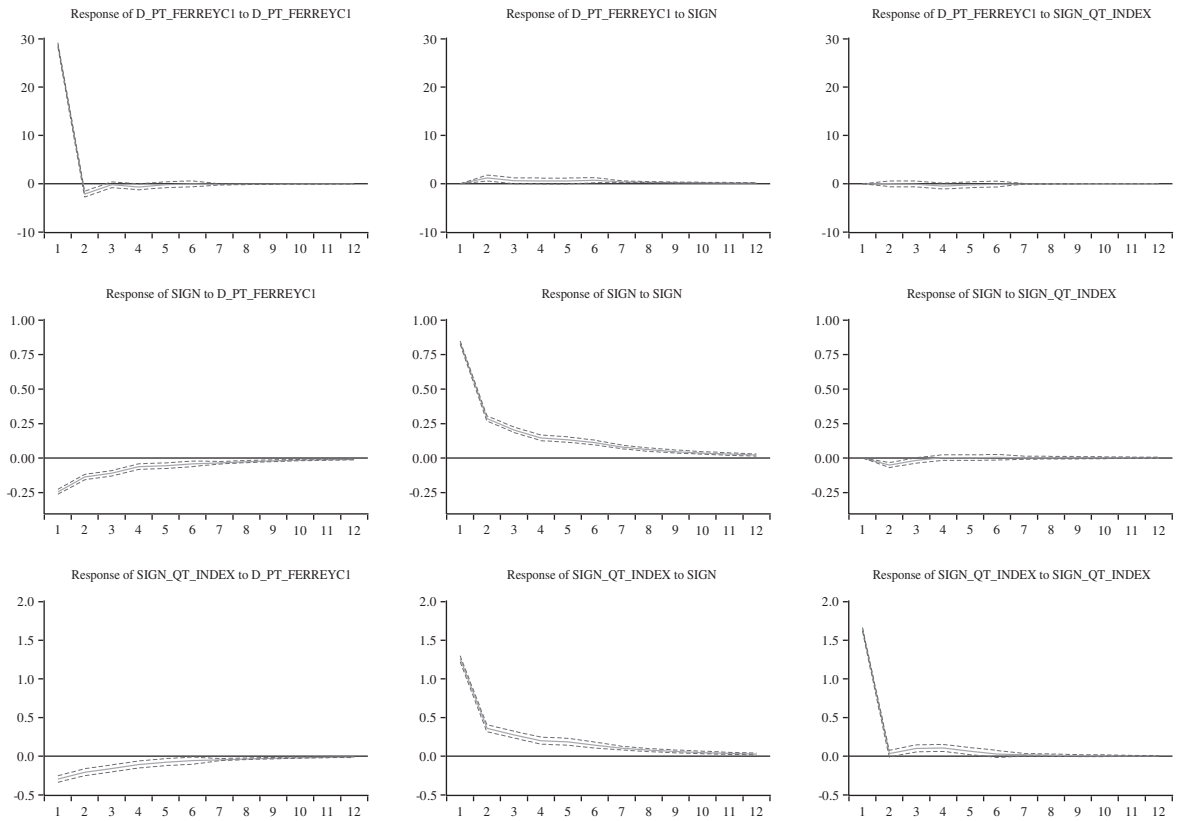
Impulse-response functions of the VAR econometric model for RIO



Source: prepared by the authors.

FIGURE B.2

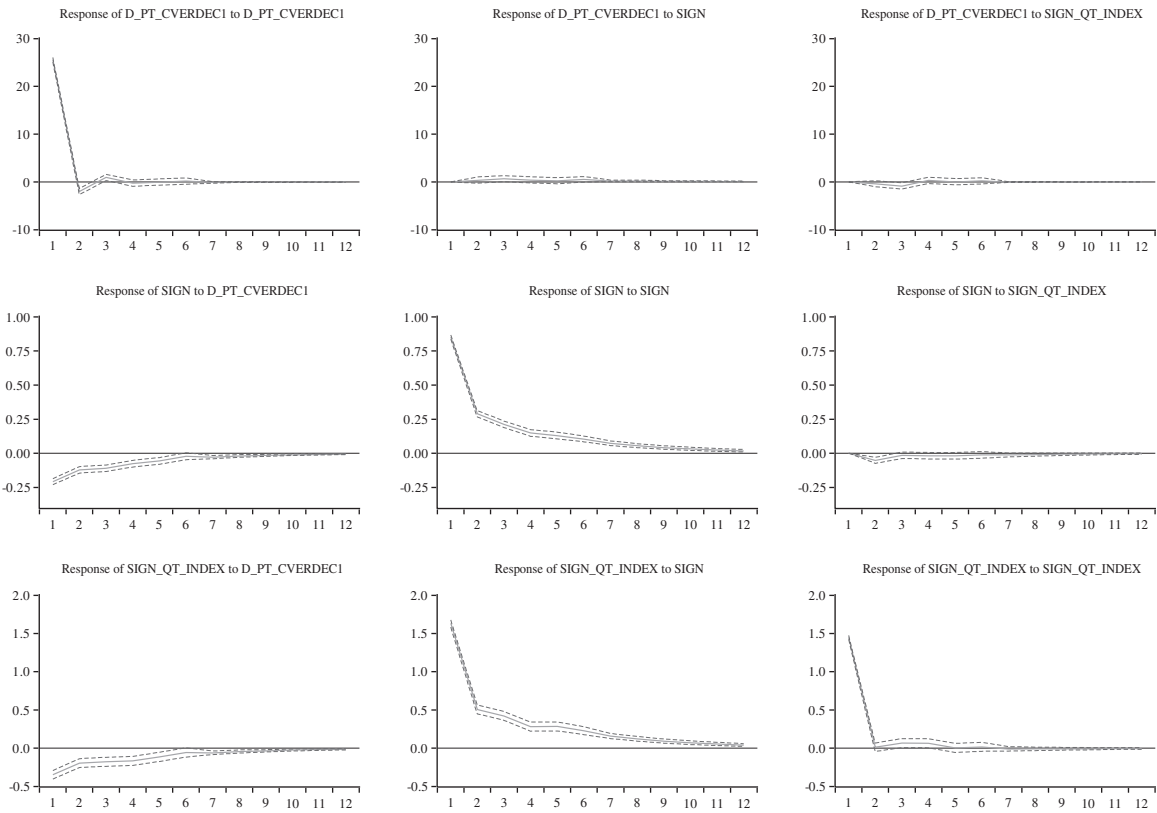
Impulse-response functions of the VAR econometric model for FERREYC1



Source: prepared by the authors.

FIGURE B.3

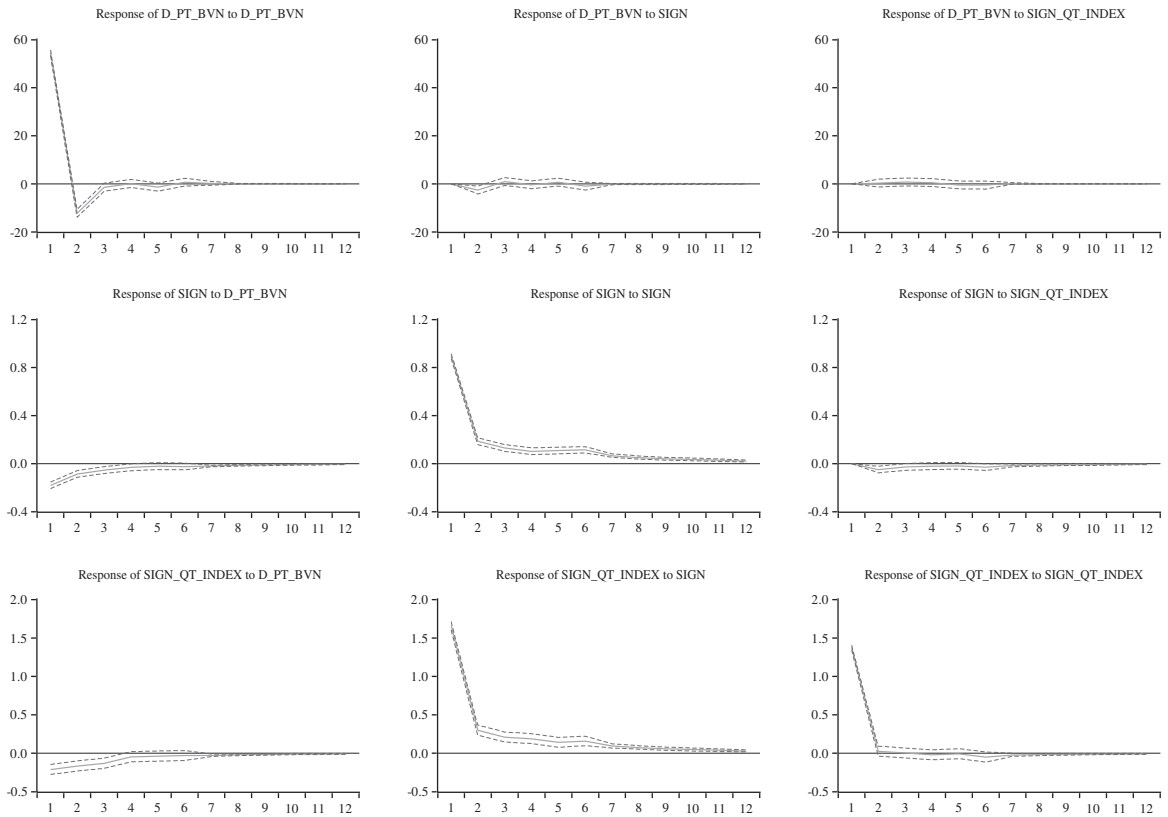
Impulse-response functions of the VAR econometric model for CVERDEC1



Source: prepared by the authors.

FIGURE B.4

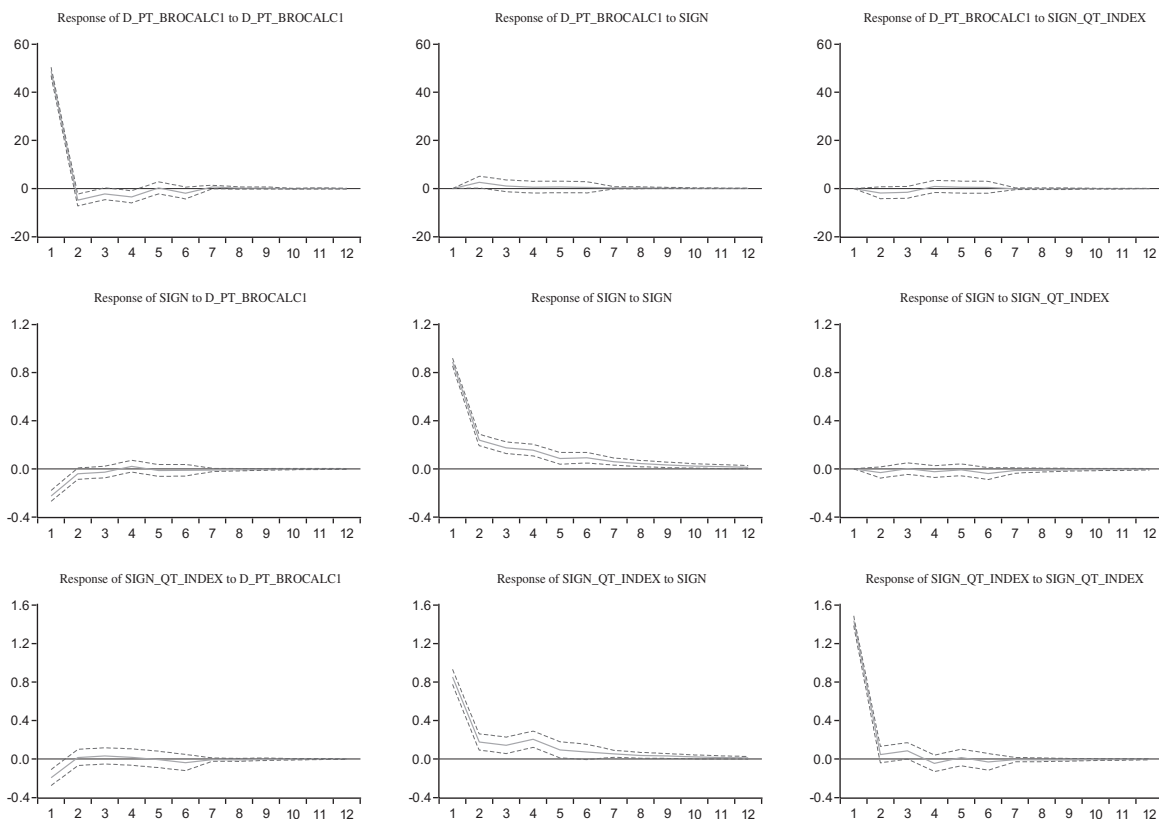
Impulse-response functions of the VAR econometric model for BVN



Source: prepared by the authors.

FIGURE B.5

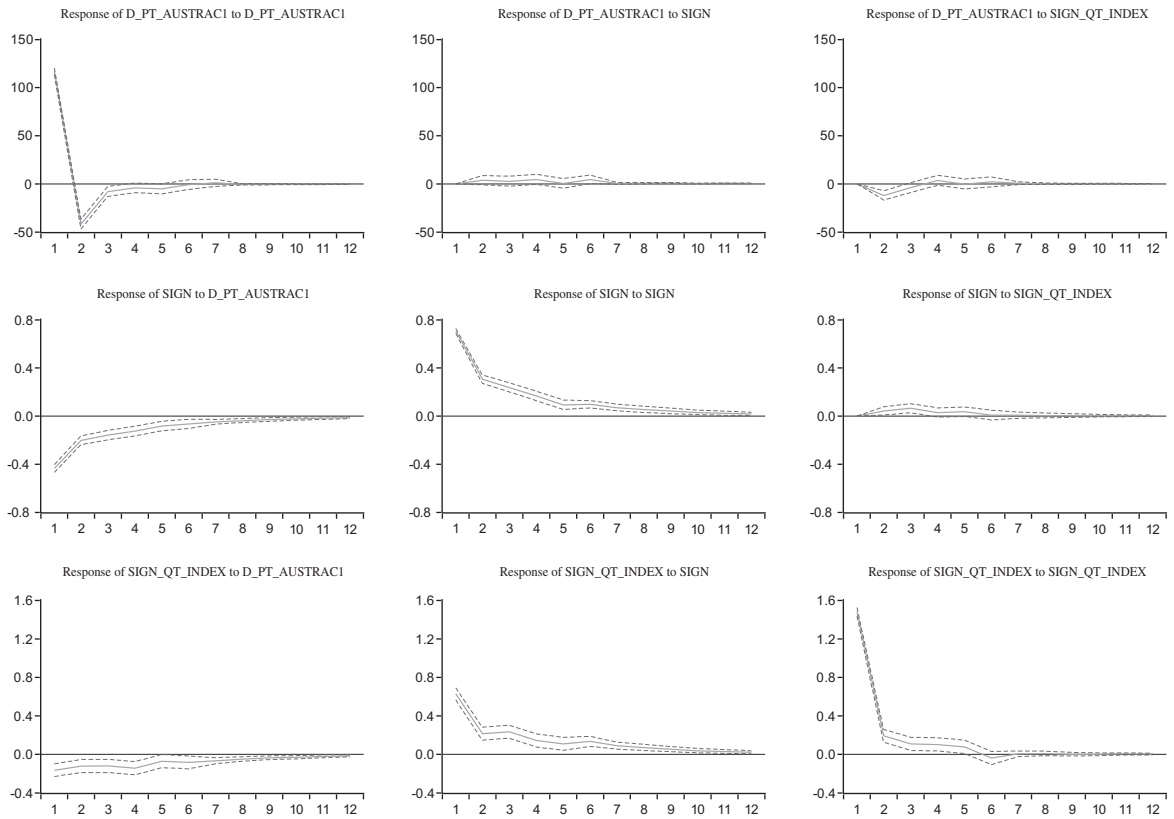
Impulse-response functions of the VAR econometric model for BROCALC1



Source: prepared by the authors.

FIGURE B.6

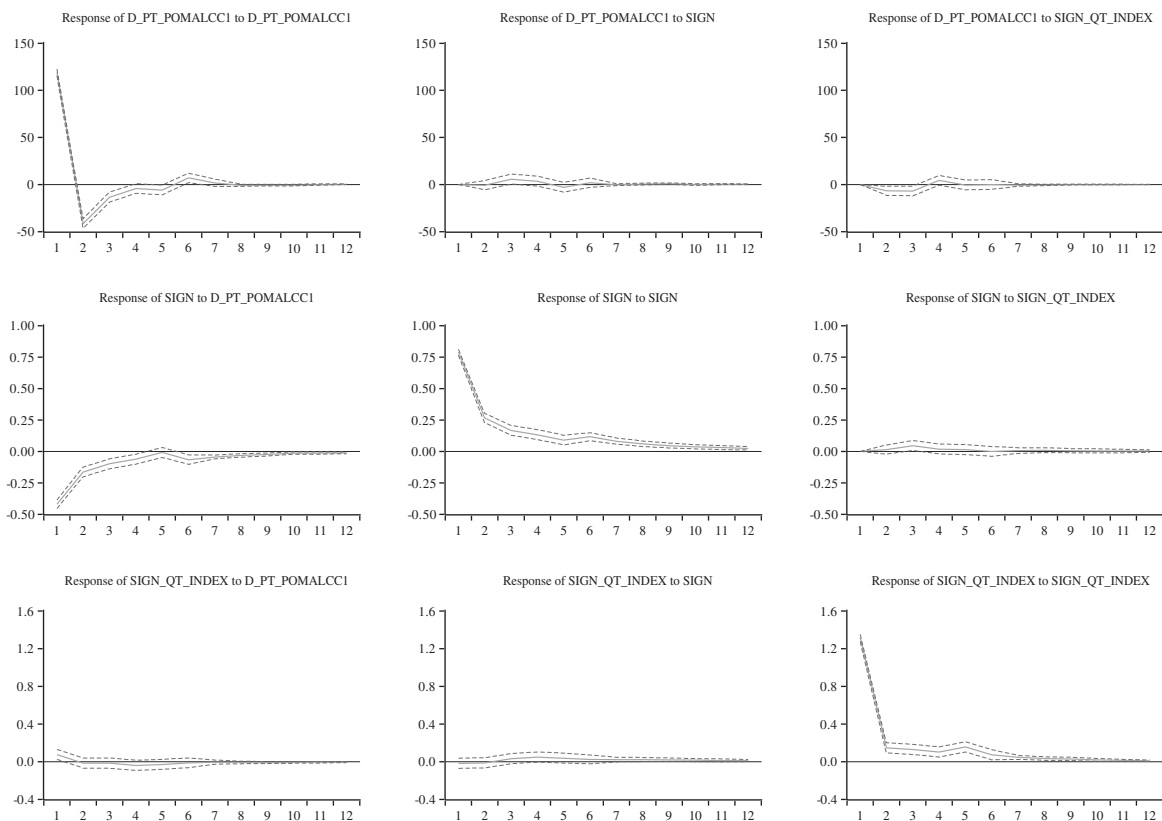
Impulse-response functions of the VAR econometric model for AUSTRAC1



Source: prepared by the authors.

FIGURE B.7

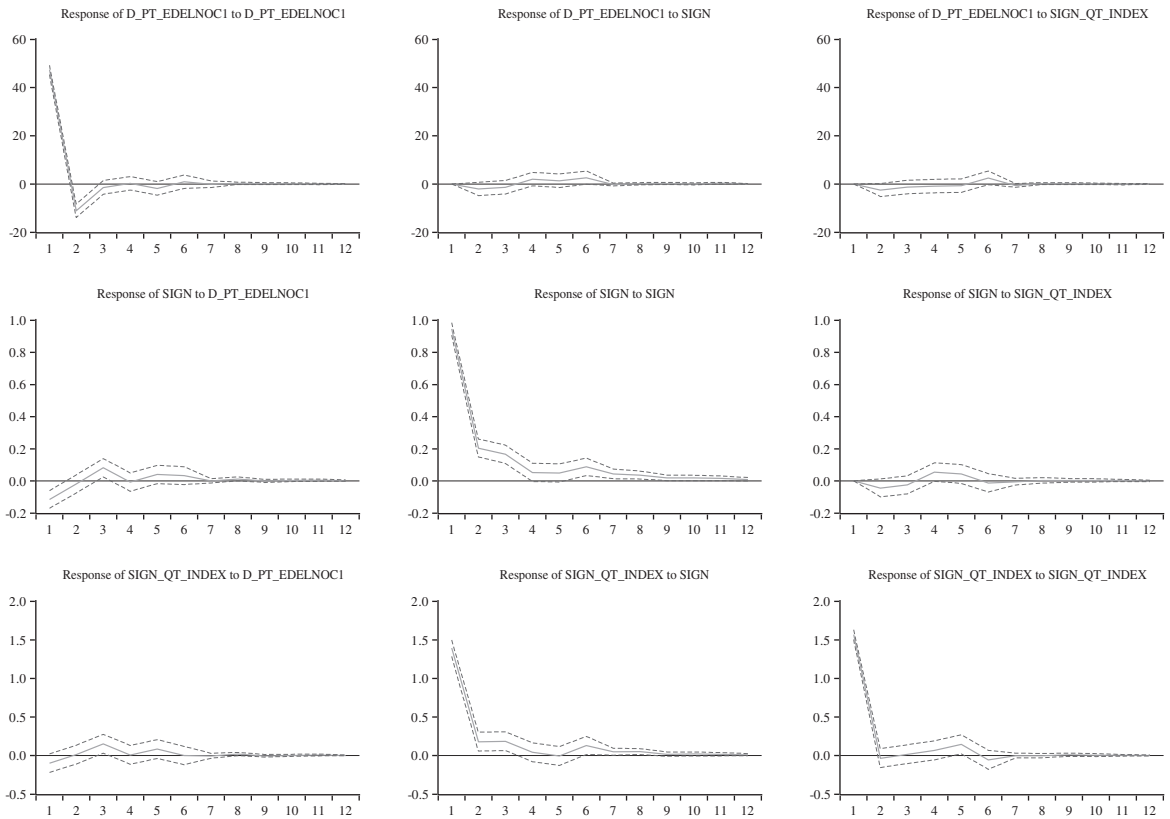
Impulse-response functions of the VAR econometric model for POMALCC1



Source: prepared by the authors.

FIGURE B.8

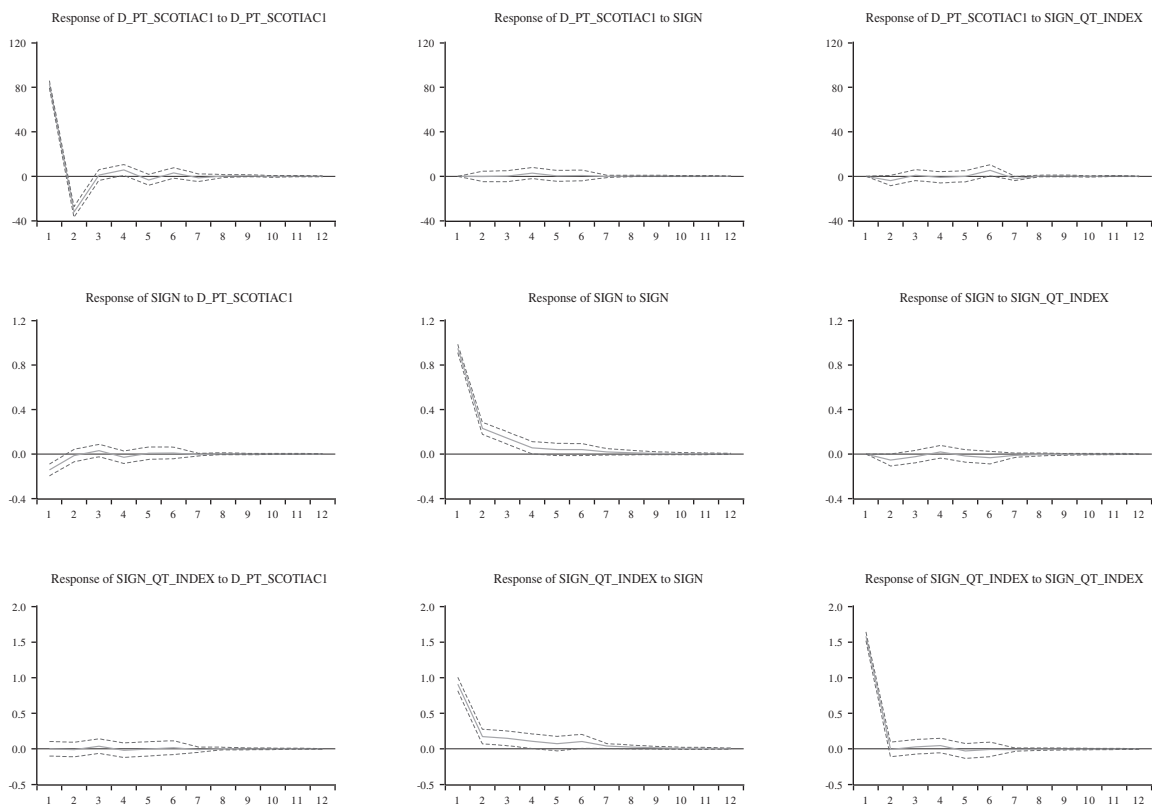
Impulse-response functions of the VAR econometric model for EDELNOC1



Source: prepared by the authors.

FIGURE B.9

Impulse-response functions of the VAR econometric model for SCOTIAC1



Source: prepared by the authors.

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