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Abstract

This paper examines the price impact of block trades for the 124 companies that comprise all listed firms in the Saudi stock market (SSM). We use high frequency intraday data (one minute intervals) for the period 2005-2008 to provide out of sample evidence of the determinants of price impact. We find an asymmetric price impact of 0.5% for block purchases and -0.38% for block sales. We document a price continuation post block trades and a price reversal after block sales. Sellers of block trades in the Saudi market pay higher liquidity premiums than buyers of block trades. However, on average, the price effect of a block trade is small and short-lived suggesting that resiliency is high in the market. Moreover, we find a direct relationship between the size of the trades and the level of information asymmetry in the market. Despite the structural differences of the SSM, the intraday pattern of price impacts is similar to patterns documented in other markets, namely an inverse J-shaped pattern. Finally, sophisticated traders can gain abnormal profits in the SSM through "free riding", a trader can benefit from the overreaction before the block trade and price reversal after the block trade.

Keywords: Price impact, Block trades, Saudi Stock Market, information asymmetry and liquidity.

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I. Introduction

The focus of this study is to analyse the determinants of the price impact of block trades in the Saudi stock market (SSM) within a market microstructure framework. Permanent, temporary and total price impacts are empirically investigated with regard to trade size category, trade sign and time of the day effects. While there have been several studies of the impact of large trades in more developed markets, covering various aspects, e.g., liquidity, transaction cost, bid-ask spreads, trading mechanism and trade size, there have been no similar studies for the SSM.

Understanding the interrelationship between trades, information and prices is at the core of market microstructure research. Moreover, exchanges and regulators who are concerned with issues like liquidity, transparency, trading processes and rules are particularly interested in volume and block trade research. Understanding the relationship between trade size and price impact can also help investors and practitioners to optimise transactions to minimise the affect of block trades on their investment performance e.g., trading in the upstairs market or splitting large orders into smaller multi-orders that are traded anonymously in the downstairs market.

The SSM is a pure order-driven market where more than ninety percent trades are initiated by private investors not institutional investors. The presence of institutional investors is a recent development. Moreover, foreign direct investment is restricted and does not entail full ownership of the shares purchased.

Since the establishment of the Capital Market Authority (CMA) in 2004, the SSM has experienced important structural reforms.[1] The need for a strong market architect is seen as crucial for the SSM and the other markets in the region. The CMA aims to promote stability and liquidity in the market through introducing regulations that encourage institutional investment and reduce information asymmetry in the market. Although documenting the features of such a rapidly changing market is an interesting story in itself the main motive of this paper is to extend the research in this area of market microstructure and provide out-of-

[1] The CMA is a newly established independent governmental agency which regulates and develops the SSM. It issues the required rules and regulations for the implementation of the provisions of Capital Market Law aimed at creating an appropriate investment environment. Its rules and regulations can be accessed in the CMA website www.cma.org.sa

sample evidence through examining a new dataset that covers all companies on the SSM at the one minute intraday level. Currently this market lacks microstructure research coverage as a result of the inaccessibility of the required trade and tick data. We attempt to examine the determinants of the price impact of block trades in the SSM to understand how this market, and perhaps similar markets, respond to large trades.[2] We focus on intraday patterns of liquidity, the cross-sectional variation effects of trading activities and the resiliency of the market following block trades.

II. Literature review

In the efficient market model, prices to change only in response to the arrival of new fundamental information. On the other hand, in market microstructure research market makers and traders also update their beliefs about the true value of security prices in response to transaction data. Hence trades themselves convey information to traders and this is a key element of asymmetric information models. Large trades, in particular, have the capacity to move prices directly through the trade itself, as well as indirectly, by influencing the trading decisions of other market participants who may observe the actions of the initiators of large trades.

The price change of a security that is attributed to trade information is the price or market impact of a trade. Market depth can be measured indirectly through examining the price impact of large trades. The higher price impacts in a less deep market pose a major challenge to stock exchanges and policy makers. How trading volume affects prices is an evolving topic that concerns institutional investors and other types of investors. Information asymmetry models consider that trade size is correlated to the probability of the trade initiator holding private information and suggest that the price impact of a trade is an increasing function of order size (Easley and O'Hara, 1987). Within an adverse selection context, block trades might signal valuable information to other traders.[3] In general, if a trader wants to buy a small volume of stock immediately then he can submit a limit order at the ask price or alternatively he can submit a market order. The transaction takes place through matching between the

[2] We use the common convention in the microstructure literature of defining block trades as any trade larger than 10,000 shares. See for example, Madhavan and Cheng (1997).

[3] Market impact studies showing the effect of trading activity on stock prices include Chan and Lakonishok, 1995, Keim and Madhavan, 1995, Chakravarty, 2001, Chiyachantana et al., 2004, Chordia and Subrahmanyam, 2004.

buyer's price and quantity and the seller's price and quantity at the ask price and this transaction price reveals the cost of immediacy. In the case of block trades, the volume available on the other side is normally not sufficient to completely satisfy the quantity demanded unless the trader is willing to jump up to the next higher ask price. In other words, to satisfy block trades investors face an unwanted upward price impact in the case of buying shares and an unfavourable downward price impact in the case of selling shares.

The price impact of block trades has been extensively analysed in the literature which normally classifies it into permanent and temporary components. The permanent component is the price change that is due to the information content of the trade while the temporary price impact is the transitory change in prices due to market frictions such as the liquidity effect and the imbalance between demand and supply.

Different approaches are used to measure the price impact of block trades. For example, an event study methodology has been used in a number of studies (see, for example, Kraus and Stoll, 1972, Holthausen et al., 1987, Keim and Madhavan, 1996). Other researchers have used time-series methodology, specifically vector autoregressive VAR-models, to test the relationship between trading volume and price movement (See, for example, Hasbrouck, 1991a., 1991b, Dufour and Engle, 2000). The VAR-model tests for dynamic changes in the model and for the duration between trades. Chan and Lakonishok (1997), Domowitz et al. (2001), Conrad et al. (2001) and Chiyachantana et al. (2004) study stock price volatility and its relationship with price impact, they find that when volatility, as a measure of dispersion in beliefs increases, it results in greater price concessions or price impact. Frino et al. (2007) measure the price impact of block trades in the Australian stock exchange using a cross-sectional regression method and adding a time of the day variable along with other variables to their theoretical model in an attempt to examine the determinants of price impact. Most of the previous models used are linear in nature, however several papers have used non-linear models to test the price impact of block trades (See, for example, Hasbrouck, 1991a, 1991b, Hausman et al., 1992, Kempf and Korn, 1999).

Chan and Lakonishok (1993) summarise three potential explanations that have been discussed in the literature for price changes caused by large trades[4] : (i) short-run liquidity cost, (ii) imperfect substitution, and (iii) the information effect (the adverse selection problem). Short-run liquidity costs occur because of demand and supply frictions at the time of the trade which may result in a price effect that is likely to be temporary. A large trader who wants to trade

[4] Scholes (1972) and Kraus and Stoll (1972) were the first to develop hypotheses on how stock prices react to block trades: the substitution hypothesis, the price-pressure hypothesis or short run liquidity costs, and the information hypothesis.

would pay a price concession for immediacy. On the other hand, liquidity providers should be compensated for taking the other side of the deal with a price concession in their favour. Large trades also move prices if there are no perfect substitutes for a particular stock. In this case, prices tend to change permanently as the buyer or seller has to offer a higher discount to make the deal attractive. Large trades are believed to convey information about the prospects of a stock. Participants in the market learn new information about the underpricing or overpricing of stocks from the decision of large traders to initiate buy or sell trades. The information effect uses the identity of traders and the size of the transaction as proxies for the information content of the trade. A permanent price change is expected to be associated with informed trading which subsequently leads to new equilibrium prices.

The majority of the empirical studies concerning block trades have documented intriguing results supporting an asymmetric price impact, where the absolute price responses for buys and sells are significantly different. The difference in price effect between block purchases and sales has been confirmed in many markets outside the US where it was first recognised and in different trading systems (see, for example, Gemmil, 1996 and Gregoriou, 2008, in the UK market; Aitken and Frino, 1996, in the Australian market and Chiyachantana et al., 2004 in a study covering 36 international markets). The general result is that buyer-initiated trades have a stronger price impact than seller-initiated trades. It indicates that block trades sellers pay a liquidity premium while buyers do not as price continuation is usually associated with block trade purchases and price reversal is associated with block trade sales. One established explanation for this phenomenon attributes it to more informed trading for purchases than for sales. Chan and Lakonishok (1993), Keim and Madhavan (1996) and Saar (2001), among others, provide an institutional explanation for this asymmetry in that the buy side is assumed to trade on information whereas the sell side trades for liquidity motives. Sell block trades can be motivated by many factors one of which is a desire for liquidity whereas buy block trades are likely to convey firm-specific information. The decision to sell a stock reflects the limited options a trader has among stocks in his portfolio, whereas the decision to buy a stock indicates a fundamental interest in that particular stock among the many stocks in the market.

Barclay and Warner (1993), Jones et al. (1994) and Dufour and Engle (2000) argue that, trading frequency should be a suitable explanatory variable to capture informed trading, as informed traders prefer to use medium size orders but more frequent trades, indicating that the number of orders might provide superior information than the size of orders. Variables other than the size and direction of the trade (buy or sell) that have been considered in studies as determinants of price impact include; stock price volatility, market condition, bid-ask spreads, turnover, firm size and momentum effects.

Institutional set up

The SSM is a relatively newly established market, officially organised in 1984, and is, by far, the biggest stock exchange in the Middle East region. According to the Arab Monetary Fund's annual report for the year ended December 2008, which provides statistics for 15 stock markets, the capitalization of the SSM represents 41% of the total market capitalisation of these markets, while the value of trades on the SSM represents 67% of the total value of stock traded in all member markets. The market value of the stocks at the end of 2008 amounts to 246.5 billion dollars down from 519.0 billion dollars in 2007. The SSM is an interesting market to examine in that relatively few companies are publicly listed and government owns a large proportion of shares, yet it is a very actively traded market. The average company size is 4.7 billion dollars, the highest in the region where the average company size over the 15 stock markets is around one billion dollars.[5] Many firms exhibit a low dispersion of shareholdings and the concentration of shares is high compared to most developed markets. Almost 45% of the total shares listed in the market are not traded because of ownership by government or semi-government entities (i.e. Pensions Fund and GOSI), foreign partners and other joint stock companies or wealthy families.[6] At the end of 2008, the free floating stocks (excluding those held by major passive shareholders and government) available for trade represented 37% of the total stock outstanding in the market.

Trading in the market is only for common stocks, there is no options market and short selling is not allowed. The distinctive characteristics of large market size and trading volume relative to the number of companies combined with the absence of institutional investors, its ongoing development and the small breadth of the market make it a unique environment to study the effect of these specific structural aspects on securities' returns and how order size effects prices. NEED

The SSM is a fully electronic pure order driven market where buyers and sellers trade through a limit order book. They provide liquidity by limit orders and demand liquidity through market orders. The SSM lacks major institutional players, who usually form the backbone of most markets. Most of the activities are initiated by private investors, with 90% of total trading initiated by individuals. The presence of institutional investors is still very new. A few

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[5] All figures are taken or calculated from the Capital Market Authority, CMA. www.cma.org.sa
[6] (SABB, Saudi Stock Market Review-2002).

government-owned pension and investment funds are the major shareholders of "blue chip" companies, however, they are passive buy-and-hold investors. Foreign investors are prohibited from direct market participation but they can enter into equity swap agreements with locally authorised brokerage companies. These arrangements give the foreign investors the right to the economics benefits of the equity but not to enjoy voting or any other rights, the dealers retain legal ownership of the shares. As for the domestic mutual funds, their total value represented only an insignificant 1.8 percent portion of the total market value of the stock market at the end of 2008. [7]

[7] The number is calculated from the Capital Market Authority, CMA

Table 1: Major Developments and Structural Changes in the Saudi Stock Market.

Year	Development and Regulation
1984	• Official start of the Saudi stock market.
1990	• ESIS (Electronic Security Information System) with completely computerized trading and settlement.
2003-2004	• Capital Market Law and Establishment of Capital Market Authority, CMA.
2006	• Foreign investors (residing in Saudi) are permitted access to the market). • New corporate governance guidance. • Stock split for the whole market (5:1), reducing par value and hence market value per share. • Change of trading times (one session per day, instead of two sessions) and change to five trading days, that is Sat-Wed as opposed to six days previously.
2007-2009	• Financial brokerage licenses are granted to brokerage houses instead of only commercial banks (The number of brokerage firms active in the market reached 35 by March, 2009.)
2008	• Calculation of the index changed to reflect only Free-Floating stocks excluding major ownership (Government, foreign partner and 10% ownership). • Reduction in the minimum variation in prices, tick size (three price band system) • Publicly displaying major shareholdings (any shareholder who owns more than 5% or more of a company) • Equity Swap Agreements with non-resident foreign investors (broker retains legal ownership, foreign investor has the economic benefits).

The newly established CMA has made dramatic alterations to the exchange in terms of regulations and structural changes to promote efficiency and liquidity. The number of firms that are traded in the market has nearly doubled over 5 years and commercial banks are no longer the only entities authorised to provide brokerage services. Now around 80 brokerage houses have been granted licenses to operate in the market.[8] The list of changes includes

[8] Thirty five were already operating at the beginning of 2009.

establishing insider trading rules and imposing fines on companies who pass deadlines to make earning announcements and alterations to trading times and tick size. Clearly all these changes will affect price formation. Therefore, an attempt to explain some aspects of SSM behaviour in a micro-structural framework should give valuable insights. Al-Suhaibani and Kryzanowsky (2000a and 2000b) are the only studies that have attempted to examine trading activities in the SSM in a market microstructure context. They find that although the SSM has a unique structure, its intraday liquidity patterns are surprisingly similar to those found in other markets although the average relative inside spread is large compared to other markets which they attribute to the tick size being relatively high. They also record that market width and depth are relatively low.

Alsubaie and Najand (2009) investigate the volatility–volume relationship in the SSM. They show strong volatility persistence and indicate that the rate of information arrival can be a significant source of conditional heteroskedasticity at the firm level. They suggest that asset price volatility is potentially forecastable with knowledge of trading volume. Nonetheless, they find that lagged volume is not significant in explaining volatility.

A report by the IMF (2006) classified the SSM as a buoyant market[9], with significant turnover and limited provision of investment information. Recently, the stock exchange has started to list major shareholders (5% or more), with the list being updated on a daily basis. Active investors can infer information about large trades through monitoring changes to this list of major shareholders.

The number of shares traded and the number of transactions have grown remarkably in the period 2001-2008 averaging 142% and 174%, PA. However the average number of shares per transaction has sharply declined from 8,873 in 2003 to just 1,144 in 2008. This decline is partially ascribed to the remarkable increase in the number of small investors who enter the market each year. The following table shows trading activities over the last 8 years.

Table 2: Summary of Some of the Main Market and Economic Indicators in Saudi Arabia

Year	GDP Billion	No. of Investors '000	No. of Shares traded	No. of transactions	Market Value in Billions	Index (Value-weighted)
2002	707	N/A	1,735	1,033	280	2,518
2003	804	N/A	5,565	3,763	589	4,437

[9] A market in which prices have a tendency to rise easily with a considerable show of strength.

2004	938	1,383	10,298	13,319	1,148	8,206
2005	1,182	2,573	12,281	46,607	2,438	16.712
2006	1,335	3,577	54,440	96,095	1,225	7,933
2007	1,430	3,669	57.829	65,665	1,946	11,176
2008	1,758	3,954	58,727	52,135	924	4,803
2009*	N/A	N/A	37,950	22.591	1,074	5,964

Notes: Source: Saudi Central Bank (SAMA), 45th Annual Report. The Saudi Arabian Riyal is effectively pegged to the dollar at a value of USD1=SAR 3.75. *2009 data for the first 6 months only.

Trading rules

Since September, 2006, trading on the SSM consists of one trading session from 11:00 AM to 03:30 PM and five trading days Saturday through Wednesday (the weekend in Saudi is Thursday and Friday). The market has four states during the day, Market Open (Order Maintenance), Market Open (Trading), Market Pre-Close and Market Close.[10] The official stock exchange (Tadawul) provides descriptions of each state and how orders are maintained, entered and executed throughout the states. [11]

Trading on the SSM uses two different forms of trading mechanism, a call auction is used to open trading in the market (maintenance and trading states) and then a continuous auction is used throughout the day (trading state). The call auction is used during the first five minutes of a day's trading to determine an opening price which is the price that maximises trading volume. Orders entered during the pre-open period are queued in the system. An opening price is recalculated every time an order is submitted in the pre-trade period until a final trading price is set at the opening. The following criteria are used to determine the opening price; share volume, minimum order imbalance and share price from the previous close. Once the allocation of volume at the opening price is complete, the market is opened for continuous trading in which limit orders are submitted by buyers/sellers and transactions take place immediately upon the availability of a counterparty order or instantly in the case of a market order. During the continuous trading period, limit orders that do not immediately match with another order on the other side are queued in the system. Orders that are queued in the system follow price and FIFO time priority. The settlement time for transactions is t+0, that is the time of transfer of ownership is the time of the transaction.

During the continuous trading period, orders must be at prices within 10% of the closing price on the previous day. This limit is set by Tadawul to control for large swings in prices during a

[10] In the old system, there were two sessions per day (10: AM-12AM and 4:30PM-6:00PM) and six trading days per week from Saturday through Thursday where Thursday had a morning session only.
[11] Stock exchange website : www.tadawul.com.sa.

day. The only exception is for new IPO's where the stock is normally allowed to move freely for the first few days of trading.

The trading mechanism followed in the SSM is very similar to the theoretical model of the electronic limit order book developed by Glosten (1994). Trade information and the status of the order book are available immediately to the public both through electronic screens in the trading rooms of the dealers and through online access for subscribers. Traders can also phone their brokers to inquire about prevailing quotes and prices, and to place orders. The limit order book is partially displayed to the public by most brokers with the five best ask/sell quotes and quantities being publically available with less than five minute time lag. However the best quotes are displayed in aggregate format (a best quote shows only the total quantity available at that quote). The status of the best quotes along with quantities is updated each time an order arrives, is cancelled or is executed.

Independent quote and trade data providers, who charge a premium for their services, can show more detailed real time quotes and have the facility to allow users to watch the order book for bids and offers – particularly the 5 best quotes by price level and 10 by orders in real time. Independent data vendors also show trade by trade data at the end of the trading day.

Investors who want to transact large block trades can choose to transact anonymously in the downstairs market through automatic routing and execution but probably face a higher price impact due to the trade size implication and adverse selection problems. As an alternative, negotiation and search takes place between buyers and sellers through personal networks of investors and dealers thus creating an informal "upstairs market"[12]. Once a buyer and a seller agree on price and volume they ask for the trade to be handled through the system. The prices of such deals may not reflect current market/firm conditions; therefore trades in the upstairs market are not integrated into the price discovery mechanism of the trading system except when they are reported by Tadawul during trading hours or sometimes at the end of the trading day. For this reason, we only consider block trades that take place in the normal automated downstairs market. Any identified "upstairs" block trade is excluded from the study, but not all these upstairs blocks are effectively identified as Tadawul does not announce off-market block trades.

Explicit direct transaction costs in the SSM are comparatively low at 0.12% of the total value of the trade levied on each party to the trade (buyer and seller) or the minimum of

[12] Sometimes the Tadawul officially sends messages to dealers in the search for counterparties. Presumably, only liquidity traders would seek help from the stock exchange to facilitate trades.

SR12 and USD 3.2 for trades less than SR10,000. Prior to September 2008 the minimum price variation unit for all shares used to be at 25 Hallalas (1 Saudi Riyal=100 Hallalas), regardless of the trading price of the share traded. This unified tick size had a severe effect on the cost of trading and market liquidity because it limits the prices that traders can quote and thus restricts price competition especially for low-priced shares. Clearly this creates return bias because stocks with relatively low prices would show higher price impact and volatility in their returns. The stock exchange, realising the problem, has introduced a new scheme where tick size is based on the share price, within three bands that are shown in the following table.

Table 3: Old and New Tick size

BANDS	Tick Sizes
New system	
BAND 1 :Shares SR25.00 or Below	**SR 0.05**
BAND 2 :Shares SR25.10 to 50.00	**SR 0.10**
BAND 3 :Shares SR50.25 and above	**SR 0.25**
Old System	**Fixed (SR 0.25) for all stocks**

This table compares the new system for tick sizes that is adopted in Sep, 2008 with old unified tick system. Source: Tadawul, USD1=S.R3.75

III. Data Processing and Descriptive Analysis

We use high frequency data (sampled at one minute intervals). The dataset is taken from Mubasher, a vendor of quotes and transaction data in the SSM. Historical prices have been aggregated on a monthly basis because data vendors only provide one month of historical data at anytime. The dataset is unique in that it includes all listed companies (124 companies) in the SSM and the market index, the Tadawul All Share Index (TASI) at the intraday level. The dataset contains all transactions which are time-stamped to the nearest minute. Any inference about the data is applicable to the whole market as the dataset is free from any sample bias. It covers almost four-years, from Jan 2005 to October 2008, with over 16,076,414 records of all transactions and bid-ask quotes. We define block trades as any trade with over 10,000 shares giving 4,221,870 trades or 20.8% of all trades in our sample. Our sample size, when compared with those used in previous studies of block trading, is very large. Frino et al. (2003) used 2,796,561 block trades in their working papers, Chan and Lakonishok (1993) examine 1,215,387 transactions while Madhavan and Cheng (1997) analyse only 16,343 blocks.

To classify trades, we use the method of Lee and Ready (1991). The idea underlying this method is to infer trade direction using the transaction price relative to the previous price, the “tick rule”, or to the quote mid-point price, the “midpoint test”. The tick rule test compares trade price changes relative to the previous trade price. If the price change between trades is positive, then the transaction is coded as a buy-initiated trade. A negative price change yields a sell-initiated trade. We follow Bonser-Neal et al. (1999) in determining how to sign a trade when the change in the price is zero. We compare trade price P(t) with the trade price P(t-2) and if the change in price is still zero, we repeat the process until we find a difference in prices or we stop the process at P(t-5). If the price change is still zero when P(t-5)) is used as the comparator then this trade is unclassified and omitted.

We conduct the midpoint test by comparing trade prices to quote midpoints prevailing at trade time calculating the midpoint between the bid and the ask quotes. The prevailing midprice corresponding to a trade is used to decide whether a trade is a buy, a sell, or unclassified. If the transaction price is higher (lower) than the midprice, it is viewed as a buy (sell). Any trade price at the midpoint will be unclassified. Although there is a possibility of misclassification, we follow this procedure as it is standard and widely accepted in the literature.

Using the “tick rule”, we classify 2,366,099 trades as buy trades and 1,855,236 as sell trades out of a total sample of 4,221,335 transactions. On the other hand, using the “midpoint test” we classify 1,714,072 trades as buy trades and 1,646,728 trades as sell trades. The total number of trades in the sample is 3,360,800 after data cleaning which is lower than the tick rule sample, because we exclude unclassified trades. Consistent with prior research, we use a trade indicator for each trade to indicate the nature of the trade: 1 (buy), −1 (sell), or 0 (undecided).

One minute intervals are used in this study, however, sometimes multiple trades take place in the same minute. We follow (Engle and Russell, 1998, and Spierdijk, 2004) and treat multiple transactions at the same time as one single transaction with aggregated trade volume and average prices.

Since the data does not provide information on the prevailing bid and ask price quotes we believe the “tick rule” should provide a more accurate trade classification algorithm than the “midpoint rule”. Lee and Ready (1991) state that “When only price data is available... the 'tick' test performs remarkably well”. However, for comparison purposes, we report the classifications from both tests and the number of trades along with the mean price impacts in table 4.

Table 4: Summary Statistics for Block Trades.

	No of trades	Avg No of shares	Price Impact%	Variance
Panel A: Trade sign classification using Tick Rule.				
All Trades	16,076,414	9,528	---	---
Block Trades (26.2%)	4,221,870	29,130	0.067	0.01323
Buy (14.7%)	2,366,099	30,046	0.491	0.01125
Sell(11.5%)	1,855,236	28,204	-0.388	0.01247
Panel B: Trade sign classification using Midpoint Rule				
Buy (10.6%)	1,714,072	27,613	0.288	0.01193
Sell (10.2%)	1,646,728	23,472	-0.193	0.01176

Notes: This table reports the number of observations in the dataset with descriptive statistics regarding the average number of shares per trade, average value, average price impact and its variance. Panel A uses the tick rule and Panel B uses the midpoint rule which shows a smaller number of observations as we exclude unclassified trades that happen at the midpoint.

Table 4 provides some descriptive statistics about the number of trades classified into buys and sells. Panel A lists the main characteristics of block trades using the tick rule. Block trades amount to 26.2% of all trades which is not high when compared to more developed markets where institutional investors play an active role in the market. However, considering the lack of institutional investment in the SSM, the fact that block trades make up one quarter of all trading volume can be considered a very high percentage. Large “off-market” trades are sometimes included in the dataset and these are hard to filter out as the reporting of these trades is not always strictly accurate as regards trade time. However, these off-market large trades do not happen frequently and for robustness, we exclude the largest 1% trades from our analysis.

14.7% of all trades are classified as buy initiated trades and 11.5% of all trades are classified as sell initiated trades. The numbers of buy trades are higher than sell trades, and this seems to be the case for stocks with larger market capitalisation (Gemmill, 1996 and Gregoriou, 2008). The mean price impact differs between the two categories, with average values of 0.491% and -0.388%, respectively. The averages suggest an asymmetry in price impacts that has been found in many previous papers. Panel B lists the number of block purchases and sales according to the “midpoint rule” after excluding the “unclassified” category. The mean price impact of block purchases (sales) is 0.288% (-0.193%). Thus the price impact asymmetry is robust when using different trade classification algorithms. Even though the price impact is higher for buy trades, the number of purchases exceeds the corresponding number of sales. One would assume that since price impact is higher for purchases implying higher trading costs, we should expect higher numbers of sales than purchases. In contrast to our results many previous studies report higher numbers of sales, on a downtick, compared with purchases, on an uptick. One explanation for the higher numbers of purchases is that it is easier to sell a large amount of stock than to buy the same amount with minimal price impact. We can imply from table 4 that the number of trades has a relationship with the price impact asymmetry in purchases and sales.

Table 5: Summary Statistics of Block Purchases and Sales for the Saudi Stock Market.

	No of trades	Avg No of shares	Avg Value Per trade	Avg Quoted Spread	Avg Relative Spread
All trades	16,076,414	9,528	58,000	0.19	0.0030
Block trades	4,221,870	29,130	1,880,473	0.3586	0.0063
Block Buys	2,366,099	30,046	1,932,452	0.3607	0.0062
Block Sells	1,855,236	28,204	1,827,466	0.3564	0.0064

Notes: Number of trades, average number of shares traded, average value per trade, average quoted spread where quoted spread is defined as the ask minus the bid price, and the average relative spread defined as the ask price minus the bid price, divided by the midprice (the average of the bid and ask prices). The exchange rate is approximately ($1=3.75 Saudi Riyal).

Table 5 provides descriptive statistics about the size and value of the trades in our sample. We analyse 4,221,870 block transactions with a total value of S.R 8.7 trillion (equivalent to $2.32 trillion) after removing transactions at the opening and IPO's trading in the first week of trading where order levels tend to be particularly high. The average number of shares per trade is larger for purchases amounting to 29,130 shares, compared to 28,204 for sales. Moreover, the average quoted spread is slightly higher for purchases at S.R 0.3607 compared to S.R 0.3564 for sales. The relative spread, shows that the spread is larger for sale trades than for buy trades; however, the difference is small.

The average quoted and relative spreads for all trades are around half of those found for block trades. The size of a trade can be seen as a proxy of the information content of the order. Easley and O'Hara (1987) indicate that informed traders prefer to trade a large amount at any given price, a finding subsequently confirmed by many other researchers. Consequently, informed trading is believed to have a greater effect on price impact and bid/ask spread.

IV. Methodology

In order to estimate the price impact of block trades, we classify the price effect of large transactions into three types following common practice in the literature.[13] Consistent with (Holthausen et al., 1990, Gemmill, 1996, and Frino et al., 2007) we use a five trades "minutes" benchmark to calculate price effects.[14] The total price impact is calculated as the percentage return from five trades prior to the block trade to the block trade itself. The temporary price impact is calculated as the percentage return from the block trade to the fifth trade after the block trade. The permanent price impact represents the percentage return from five trades prior to the block trade to five trades after the block trade. Because quotes data are not directly available in the SSM, all prices used in the computations are transaction prices. The following equations represent the three types of price effect:

$$Total\ Impact = (close - close_{-5}) / close_{-5} \tag{1}$$

$$Temporary\ Impact = (close_{+5} - close) / close \tag{2}$$

$$Permanent\ Impact = (close_{+5} - close_{-5}) / close_{-5} \tag{3}$$

We mainly follow the model of Frino et al. (2007) where the price impact of a block trade is a function of a number of variables that are thought likely to be the determinants of the price effect. The following regression is estimated:

$$\text{Price Impact} = \alpha + \beta_1 \text{lnSize} + \beta_2 \text{Volatility} + \beta_3 \text{lnTurnover} + \beta_4 \text{MarketReturn} + \beta_5 \text{Momentum} + \beta_6 \text{BAS(relative)} + \varepsilon \tag{4}$$

[13] Within asymmetric information models, the permanent price impact of a large trade is due to new information conveyed by the trade, while the temporary price impact is associated with liquidity shortages. For in depth analysis, refer to Holthausen et al., 1987, Glosten and Harris, 1988, Chan K. and Lakonishok, 1995, among many others.

[14] Since we use intraday data collected every minute, we use the terms "trades" and "minutes" interchangeably.

Where the variables on the right hand side of the equation are defined in the following way:

1- ln(size) is the natural logarithm of the number of shares traded (Volume) reported to the nearest minute. Trade size is used as a proxy of the information content of the order, an informed trader would only sell when he believes the stock is overpriced and buy when the stock is underpriced. We expect size to have a direct effect on price movement. See for example, Easley and O'Hara (1987).

2- Volatility is the standard deviation of trade to trade prices on the trading day prior to the block trade. We include the standard deviation of the transaction price as a measure of intraday volatility to capture the variation in true prices of the stock. Volatility represents dispersion in beliefs among traders, hence it is an indirect measure of adverse selection. An increase in the volatility of a stock will increase its market risk, therefore, traders will demand higher compensation in the form of price concessions. Thus we expect that more volatile stocks will have higher price impact (see, Domowitz et al., 2001).

3- ln(turnover) is the natural logarithm of the total monetary value of stocks traded divided by the value of shares outstanding on the trading day prior to the block trade, using the following ratio, turnover = value of shares traded/value of shares outstanding. Turnover is used as a measure of liquidity in the market. Many researchers use turnover as their sole measure for trading activity or market liquidity. For example, Lakonishok and Lev (1987) and Hu (1997) suggest that turnover is a good measure of liquidity. We anticipate that turnover will be negatively related to the price impact of block trades.

4- BAS represents the bid-ask spread which is another measure of liquidity. Both relative and effective spreads are used in the analysis. Relative spread is the proportional bid–ask spread immediately prior to the block order being released to the market, calculated as the following:

$$\textit{Relative Spread} = (\textit{High} - \textit{Low})/(\textit{High} + \textit{Low})/2 \tag{5}$$

The effective spread is the difference between the transaction price and the midpoint of the bid and asks prices multiplied by two to show the actual round-trip transaction costs. The effective spread is calculated for a round trip trade using the following equation:

$$\textit{Effective Spread} = 2(\textit{trade price} - \textit{mid price}) \tag{6}$$

When liquidity is high, bid ask spreads tend to be tight, thus we expect a positive relationship to exist between bid-ask spread (BAS) and price impact.

5- Market Return represents the daily return on the Tadawul All Shares Index (TASI) which covers all listed companies in the market. We follow Aitken and Frino (1996) and Bonser et al. (1999) in using the market return on the day of the block trade. A positive relationship is expected to exist between market return and price impact. WHY?

6- Momentum is calculated as the lagged cumulative daily return for the stock on the five trading days prior to the block trade. It indicates whether there is a buying or selling trend for a particular stock. We follow Saar (2001) in differentiating between the price impact for a stock when it is at the beginning of a price run-up and after a long price run-up. He suggests that past price performance, represented by cumulative lagged returns, affects the magnitude of price impact. Since there is some evidence of herding in the market, we expect a positive relationship between momentum and price impact.

7- Time dummy variables. These dummy variables were constructed to analyze whether there are systematic intraday variations in the magnitude of block trade price impact. A day is divided into three time intervals. As the trading hours of SSM are 11:00 –15:30, we classify time as follows: the first trading hour (11:00-12:00), midday trading (12:00-14:30) and the last trading hour (14:30-15:30). Dummy variables representing each of the three intervals of the trading day are used in the analysis.

V. Regression Results and Analysis

Table 6 presents the estimated parameters from the regression for the entire sample, (4,221,870 block transactions). Panel A reports the mean price effect of the independent variables using the three types of price impact permanent, total and temporary. On average, the temporary effect is only -0.108% whereas the total effect is -0.096%. The temporary impact as a measure for immediate demand effects shows that immediacy is not highly priced in the SSM indicating a high depth for the market. Hence, liquidity (non-informational) trades have a very low level of price impact on stocks.

The permanent impact is roughly ten times larger than the temporary effect at -1.08%. The SSM seems to be very sensitive to potentially informed trades. Panel B presents the regression results for the estimated coefficients of the explanatory variables. All the coefficients are significantly different from zero at the 1% level. The size of the trade has a direct positive effect on the price impact. Volatility increases market risk for traders therefore, as expected, higher volatility increases price impact. Turnover has a negative relationship with price impact, indicating that increased liquidity in the market reduces the price impact of a block trade. Market return has a positive effect on price impact with a higher market return indicating greater price impact. Finally, momentum return which is the cumulative five day return prior to a block trade, shows a negative significant relationship with temporary and permanent price impacts. When liquidity is high, the spread tends to be narrow; however, we find that BAS has a negative relationship with permanent price impact and a positive relationship with temporary price impact. The wider spreads have a positive relationship with temporary price impact.

Our results thus provide some evidence that permanent price impact increases with larger trades, higher volatility and positive market returns. On the other hand, permanent price impact decreases when the stock is actively traded, relative spreads are higher and when the stock has a momentum trend in its returns.

Table 6: Determinants of Price Impact for Block Trades

VARIABLES	Permanent effects	Total effects	Temporary effects
Panel A: Price Effect			
Mean Return	**-0.0108*** **	**-0.00965*** **	**-0.00115*** **
Panel B: Regression Results			
Ln(size)	**0.00106*** **	**0.000957*** **	**9.89e-05*** **
	(7.32e-06)	(5.87e-06)	(5.36e-06)
Volatility	**0.000368*** **	**0.000439*** **	**-6.14e-05*** **
	(8.93e-06)	(7.16e-06)	(6.53e-06)
Ln(turnover)	**-0.000147*** **	**-0.000121*** **	**-2.93e-05*** **
	(3.36e-06)	(2.69e-06)	(2.46e-06)
Mktreturn	**0.0663*** **	**0.0370*** **	**0.0293*** **
	(0.000288)	(0.000231)	(0.000211)
Momentum	**-0.000264*** **	**-0.000346*** **	**7.13e-05*** **
	(3.15e-05)	(2.53e-05)	(2.31e-05)
BAS(relative)	**-0.0392*** **	**-0.0604*** **	**0.0276*** **
	(0.00110)	(0.000880)	(0.000803)
Observations(All)	**4,221,870**	**4,221,870**	**4,221,870**
R-squared	**0.018**	**0.013**	**0.005**

Notes: This table shows the results of the regression of the determinants of the price impact of block trades. The dependent variable, price impact, is one of three types: permanent, total and temporary price effects. We use the following model:

Price Impact = $\alpha + \beta_1$lnSize + β_2Volatility + $\beta_3$lnTurnover + β_4MarketReturn + β_5Momentum + β_6BAS(relative) + ε

Size is the natural logarithm of the number of shares per trade, volatility is the standard deviation of trade to trade prices on the trading day before the block trade takes place, turnover is the natural logarithm of the total stock turnover on the trading day prior to the block trade, BAS is the bid-ask spread (relative to the midpoint between bid and ask) at the time of the block trade. Market Return is the TASI return on the day of the block trade. Finally Lagged Return is the cumulative return of the stock in the five days preceding the block trade. Standard errors in parentheses.

*** Significant at the 1% level.

Using Effective Spread

We run the same regression model replacing the relative spread with the effective spread as the effective spread reflects the actual round-trip cost for a trader relative to a midpoint price between the bid and ask prices.

Table 7: Determinant of the Price impact Using Effective Spread.

VARIABLES	Permanent effects	Total effects	Temporary effects
Ln(size)	**0.000997*** **	**0.000871*** **	**0.000125*** **
	(7.14e-06)	(5.73e-06)	(5.22e-06)
Volatility	**0.000266*** **	**0.000421*** **	**-0.000155*** **
	(9.64e-06)	(7.73e-06)	(7.05e-06)
Ln(turnover)	**-0.000138*** **	**-0.000116*** **	**-2.54e-05*** **
	(3.37e-06)	(2.70e-06)	(2.46e-06)
Mktreturn	**0.0673*** **	**0.0382*** **	**0.0289*** **
	(0.000287)	(0.000230)	(0.000210)
Momentum	**-0.000211*** **	**-0.000264*** **	**3.28e-05**
	(3.15e-05)	(2.52e-05)	(2.30e-05)
BAS(effective)	**0.000238*** **	**-0.000280*** **	**0.000597*** **
	(1.80e-05)	(1.45e-05)	(1.32e-05)
Constant	**-0.0104*** **	**-0.00902*** **	**-0.00134*** **
	(7.54e-05)	(6.04e-05)	(5.51e-05)
Observations	**4,221,870**	**4,221,870**	**4,221,870**
R-squared	0.018	0.012	0.005

Note: this table shows estimates of the price impact regression using effective spread. All three types of price impacts have been reported here, permanent, total and temporary.

Price Impact = $\alpha + \beta_1$lnSize + β_2Volatility + $\beta_3$lnTurnover + β_4MarketReturn + β_5Momentum

+ β_6BAS(effective) + ε

All variables are as defined in table 6. Except "BAS" relative spread is replaced by effective spread which is defined as two times the deviation of transaction prices from the midpoint prices at the time of the block trade. Standard errors in parentheses. *** Significant at the 1% level

Effective spread is thought to be a better estimate of the true cost of trading because it measures how a stock was traded relative to the midpoint and whether this trade price is in favour of the trader or not – the concept of " price improvement". Effective spread also measures the tendency of block trades to move prices, the "price impact" of the trade as it uses actual execution prices.

The estimates of the parameters in the regression are presented in table 7 for the entire sample for all three types of price impact permanent, total and temporary. The estimates of the coefficients of the volume, volatility, turnover, market return, momentum returns and finally effective spread variables in the regression are all significant, and their signs, are generally consistent with prior empirical research. The trade size, volatility, BAS and market return variables all have a positive and significant relationship with permanent price impact with market returns being the most important explanatory variable for price impact which is consistent with Frino et al. (2007). On the other hand, turnover and momentum returns show negative coefficients indicating liquidity in the market mitigates price impact and that a higher price run-up increases the probability of a price reversal. The coefficient of effective spread (BAS), differs substantially from that of the relative spread in table 6 in sign and strength. Effective spread has a positive and significant relationship with price impact which is in line with the conjecture that a wider spread should cause a higher price impact.

In keeping with the existing literature, the price impact of buy and sell transactions are investigated separately to explore the possibility that their regression coefficients differ significantly. The following section discusses the relationship between price impact and trade sign.

Price Impact and Trade sign

The block purchase transactions in Panel A of Table 8 have a mean return for the permanent price impact of -1.43% compared to -0.38% for the transitory effect. We mentioned earlier that the SSM seems to be more sensitive to informed trades, which have a permanent effect on the price impact, than to liquidity trades which have a transitory effect on stock prices. With regards to the sell transactions in Panel B of Table 8, the mean permanent price impact is 0.0206% while the temporary price impact is 0.237%.

The estimated coefficients for the explanatory variables are all significantly different from zero at the 1% level. Size (trade volume) coefficients are significantly positive for block purchases and significantly negative for block sales. The size of the trade coefficients show, as the literature suggests, a direct positive effect on the price impact, the larger the volume the greater the effect. Volume has both transitory and permanent effects on prices with mean volume conveying information to the market and other traders changing the perceived market value of a stock according to volume traded. The price impact is an increasing function of trade size.

Volatility, as measured by the standard deviation of returns, represents the market risk faced by traders, therefore higher volatility is expected to have a positive relationship with price impact. Volatility shows a positive coefficient for the buy block trades and a negative coefficient for sell trades which confirms the greater price impact that is attributed to higher risk and dispersion of beliefs among traders. The volatility coefficients are consistent with prior research (e.g. Chan and Lakonishok, 1997; Chiyachantana et al., 2004; Frino et al., 2007).

Turnover has a negative relationship with price impact for buy blocks, indicating that increased liquidity in the market reduces the price impact of a block trade. Our results confirm prior research in this respect. The negative relationship between liquidity and price impact can in part be linked to a more general relationship between stock returns and liquidity. For example, Hu (1997) argues that turnover is a useful measure of liquidity and a negative relationship between stock returns and turnover exists. Brennan and Subrahmanyam (1996) also find a negative relationship between expected returns and liquidity. Conversely, block sales have a negative turnover coefficient, indicating that increased liquidity induces greater price impact. Large block sales combined with highly actively traded stocks might convey negative information because they reflect the likely action of informed traders and induce more selling which increases the price effect of these trades.

The market return has a positive coefficient for both block purchases and sales. Our market return coefficients are consistent with Frino et al. (2007) which reports positive coefficients for both buy and sell subsamples.

A stock that has shown a momentum trend in its performance is expected to have a lower price impact for block trades, the 'price-run up effect'. The momentum in price returns has a negative (positive) coefficient with the price impact for the block purchases (sales), indicating a lower price impact following a price trend. Our result lends support to Saar (2001) who finds that a recent large price run-up of a stock leads to a lower price impact for both block purchases and sales. Chiyachantana et al. (2004) report that institutional purchases of stocks after several days of price run-up induce smaller permanent price changes. Moreover, the momentum variable for the sell transactions shows a positive relationship with regard to the temporary price effect (negatively signed coefficient) and a negative relationship with the permanent price impact (positively signed coefficient). This reverse in the sign of the momentum variable indicates price reversals associated with block sales.

Finally, we find that BAS has a positively and significant coefficient for buyer initiated block trades and a negative and significant coefficient for seller initiated block trades. When the spread is wider the price impact is greater for both buy and sell block trades. Our BAS coefficients are consistent with Aitken and Frino (1996), Gemmil (1996) and Frino et al. (2007).

Our results thus provide evidence that the permanent price impact of block purchases increases following larger trades, reduced liquidity, higher volatility and market returns. The permanent price impact is decreased when the stock is actively traded and when it has established a weekly trend in its price momentum. In contrast, the permanent price impact of block sales increases when associated with larger trading volume, higher volatility and high turnover. The coefficients for market returns and momentum for block sales suggest that price impact is decreased when there are higher market returns or when a stock has recently experienced a trend in its returns performance. It is worth mentioning that the total price effect has the highest adjusted-R among the other price impacts measures for both buy and sell block trades. Total price impact is calculated from five minutes before the execution of the block trade and it suggests that the SSM is very quick in incorporating block trade information into prices. Once a block order, either sell or buy, is displayed on screens, the market reacts immediately with a greater price impact followed by a price reversal once the trade has been executed.

Table 8: Price Impact Estimates and Trade Sign (buy and sell block trades)

	Panel A: Buy			Panel B: Sell		
	Permanent effects	Total effects	Temporary effects	Permanent effects	Total effects	Temporary effects
Ln(size)	**0.00152*** **	**0.00114*** **	**0.000382*** **	**-0.0009 *** **	**0.000145*** **	**-0.000246*** **
	(8.79e-06)	(6.54e-06)	(6.69e-06)	(1.10e-05)	(8.10e-06)	(8.63e-06)
Volatility	**0.00157*** **	**0.00141*** **	**0.000169*** **	**-0.000568*** **	**-0.000172*** **	**-0.000389*** **
	(1.16e-05)	(8.62e-06)	(8.82e-06)	(1.28e-05)	(9.48e-06)	(1.01e-05)
Ln(turnover)	**-0.000311*** **	**-0.000366*** **	**4.91e-05*** **	**-0.000362*** **	**-7.54e-05*** **	**-0.000294*** **
	(1.04e-05)	(7.70e-06)	(7.88e-06)	(1.12e-05)	(8.29e-06)	(8.83e-06)
Mktreturn	**0.0361*** **	**0.0106*** **	**0.0252*** **	**0.0750*** **	**0.0368*** **	**0.0385*** **
	(0.000364)	(0.000271)	(0.000277)	(0.000406)	(0.000301)	(0.000320)
Momentum	**-0.000514*** **	**-0.00114*** **	**0.000606*** **	**0.00053*** **	**0.000483*** **	**-0.000459*** **
	(4.13e-05)	(3.07e-05)	(3.15e-05)	(4.27e-05)	(3.16e-05)	(3.37e-05)
BAS(relative)	**0.247*** **	**0.361*** **	**-0.109*** **	**-0.327*** **	**-0.507*** **	**0.188*** **
	(0.00139)	(0.00103)	(0.00106)	(0.00154)	(0.00114)	(0.00122)
Constant	**-0.0143*** **	**-0.0104*** **	**-0.00378*** **	**-0.000206* **	**-0.00251*** **	**0.00237*** **
	(8.96e-05)	(6.66e-05)	(6.82e-05)	(0.000111)	(8.23e-05)	(8.77e-05)
Observations	**2366099**	**2366099**	**2366099**	**1855236**	**1855236**	**1855236**
R-squared	0.045	0.089	0.009	0.054	0.117	0.020

Notes: The table presents estimated parameters separately for the buy and sells subsamples. We use the tick test for trade classification. Buyer initiated trades (2,366,099 observations) are reported in panel A and seller initiated trades (1,855,236 observations) are reported in panel B. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 9: Price Impact Estimates and Trade Sign using Effective Spread

	Panel A: Buy			Panel B: Sell		
	Permanent effects	Total effects	Temporary effects	Permanent effects	Total effects	Temporary effects
Ln(size)	**0.00175*** **	**0.00149*** **	**0.000262*** **	**-0.000542*** **	**-0.000541*** **	**1.08e-06**
	(8.57e-06)	(6.38e-06)	(6.54e-06)	(1.07e-05)	(8.08e-06)	(8.43e-06)
Volatility	**0.000873*** **	**0.000536*** **	**0.000340*** **	**-0.000255*** **	**0.000421*** **	**-0.000679*** **
	(1.25e-05)	(9.28e-06)	(9.52e-06)	(1.38e-05)	(1.04e-05)	(1.08e-05)
Ln(turnover)	**-0.000276*** **	**-0.000329*** **	**4.80e-05*** **	**-0.000385*** **	**-0.000122*** **	**-0.000270*** **
	(1.03e-05)	(7.70e-06)	(7.90e-06)	(1.13e-05)	(8.48e-06)	(8.85e-06)
Mktreturn	**0.0324*** **	**0.00503*** **	**0.0270*** **	**0.0814*** **	**0.0465*** **	**0.0351*** **
	(0.000363)	(0.000270)	(0.000277)	(0.000407)	(0.000306)	(0.000319)
Momentum	**-0.000860*** **	**-0.00164*** **	**0.000759*** **	**0.000483*** **	**0.00118*** **	**-0.000713*** **
	(4.12e-05)	(3.07e-05)	(3.15e-05)	(4.29e-05)	(3.23e-05)	(3.37e-05)
BAS(effective)	**0.00472*** **	**0.00620*** **	**-0.00142*** **	**-0.00353*** **	**-0.00594*** **	**0.00251*** **
	(2.38e-05)	(1.77e-05)	(1.82e-05)	(2.43e-05)	(1.83e-05)	(1.90e-05)
Constant	**-0.0159*** **	**-0.0130*** **	**-0.00293*** **	**0.00324*** **	**0.00277*** **	**0.000448*** **
	(8.85e-05)	(6.59e-05)	(6.76e-05)	(0.000110)	(8.30e-05)	(8.67e-05)
Observations	**2366099**	**2366099**	**2366099**	**1855236**	**1855236**	**1855236**
R-squared	0.048	0.089	0.008	0.042	0.076	0.017

Estimates of the price impact regression using Effective spread. We use the same model as previously but with effective spread as the dependent variable. All variables have been defined in table 6. The effective spread "BAS", is defined as two times the deviation of the transaction price from the midpoint prices at the time of the block trade. The sample is classified into buy blocks and sell blocks according to tick rule. Standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Price Impact and Trade sign using Effective Spread

Table 9 reports the same OLS regression model using effective spread instead of relative spread. Effective spread is a measure of the tendency of trades to move prices, known as "price impact", as it uses actual execution prices. The estimated coefficients using effective spread do not change significantly from the previous model using relative spread. The main difference is that the constant coefficient is positive and significant for block sales and negative and significant for block purchases. Both the relative and effective spread models have a positive relationship with permanent price impact for both the buy and sell subsamples. Nonetheless, the temporary effect has an opposite relationship with the bid-ask spreads (BAS), relative and effective spreads. When liquidity is low BAS tends to be higher, therefore, BAS should be positively associated with price impact. But in the case of temporary effects, which measure the transitory and liquidity related effects of a block trade, the relation is negative. BAS has negative and significant coefficients for block purchases and positive and significant coefficients for block sales. The less liquid a stock is, the lower the temporary price impact. This result appears odd as liquidity providers should impose a liquidity premium on large orders. BAS and turnover are two proxies for liquidity in the market, both indicate that the more liquidity a stock shows, the greater the transitory price effect. One explanation of the relationship between liquidity and temporary price impact is that the SSM overreacts to block trades once an order is entered into the book as reflected in the higher total impact. A price reversal is expected once the block order has been executed, which can be seen from the opposite signed coefficients for the temporary price impact. Uninformed traders can misinterpret large trades and assume they always contain valuable information.

An informed or sophisticated trader could benefit from such overreaction in prices and gain abnormal returns. Moreover, the temporary price impact is closely related to the bid-ask bounce in prices, the bounce back in prices after block trades is observed in both buy and sell trades, however, the magnitude of the price reversal is higher for sell trades (liquidity premium).

Time of the day effect

Many empirical research papers have reported that spreads show a U shaped pattern throughout the day. Spread, a measure of liquidity, tends to be wider and depth tends to be lower toward the beginning and end of the day. Since price impact is another liquidity cost, we expect that block trades occurring at the beginning or end of the trading day will have a higher price impact. To investigate whether there are any systematic intraday variations in the magnitude of block trade price impact, a trading day is divided into three time intervals: the first hour, midday and the last trading hours. The details of SSM trading hours and how the trading day is divided into three intervals are discussed in the methodology section.

Table 10: **Price Impact and the Time of the Day Effect.**

	All	Buy	Sell
Ln(size)	**0.000988*** **	**0.00175*** **	**-0.000539*** **
	(7.12e-06)	(8.56e-06)	(1.07e-05)
Volatility	**0.000321*** **	**0.000914*** **	**-0.000260*** **
	(9.85e-06)	(1.25e-05)	(1.39e-05)
Ln(turnover)	**-0.000338*** **	**-0.000229*** **	**-0.000363*** **
	(8.22e-06)	(1.05e-05)	(1.15e-05)
Mktreturn	**0.0672*** **	**0.0324*** **	**0.0814*** **
	(0.000287)	(0.000362)	(0.000407)
Momentum	**-0.000250*** **	**-0.000913*** **	**0.000476*** **
	(3.14e-05)	(4.12e-05)	(4.29e-05)
BAS(effective)	**0.000218*** **	**0.00463*** **	**-0.00351*** **
	(1.81e-05)	(2.39e-05)	(2.44e-05)
TimeDum1	**0.000364*** **	**0.000504*** **	**0.000273*** **
	(1.73e-05)	(2.15e-05)	(2.51e-05)
TimeDum2	**0.000168*** **	**-0.000243*** **	**0.000694*** **
	(1.50e-05)	(1.86e-05)	(2.18e-05)
Constant	**-0.0100*** **	**-0.0159*** **	**0.00277*** **
	(7.44e-05)	(8.98e-05)	(0.000112)
Observations	**4221870**	**2366099**	**1855236**
R-squared	0.018	0.049	0.042

Notes: This table lists the estimated coefficients for the cross-section price impact model for the entire sample and for the subsamples, buys and sells. Model used:

Price Impact = $\alpha + \beta_1$lnSize + β_2Volatility + $\beta_3$lnTurnover + β_4MarketReturn + β_5Momentum + β_6BAS(effective) + β_7TimeDum1 + β_8TimeDum2 +ε

All variables have been defined in the previous analyses. TimeDum1 is a dummy variable that assigns the value of 1 for all block trades that took place in the first trading hour, otherwise 0. Timedum2 is a dummy variable taking the value of 1 for all bock trades occurring during the mid trading day period, otherwise 0. Timedum3 is the reference group, which is a dummy variable for all block trades recorded during the last trading hour and takes the value of 0. *** Significant at the 1% level.

Each interval is assigned a dummy variable that takes the value of 1 if the trade takes place in that interval, otherwise it takes the value of zero. TimeDum1 and TimeDum2 represent the first trading hours and midday trading hours, respectively. The last trading hours (TimeDum3) is the reference group for our analysis and is therefore omitted from the regression. The coefficients of the other two dummy variables represent the difference in price impact behaviour in these periods compared to the reference group.

The price impact of buyer initiated trades tends to decrease as time passes. The highest impact is found in the first trading hours where the coefficient is positive and significant. Trading during the day has the lowest price impact amongst the three categories. We can infer that informed trading is highest at the beginning of the day and, as trading continues, the information asymmetry decreases or is incorporated into the prices. The closest pattern to resemble the SSM price impact behaviour across the day is the reverse J-shape, similar to that found by McInish and Wood (1992) who find patterns in bid-ask spreads and the time of the day dummy variables coefficients. Our time of the day results also coincide with those of Frino et al. (2007) who find price impact is largest for block trades executed in the first hour. Moreover, the intraday spread pattern found by Al-Suhaibani and Kryzanowski (2000a) in the SSM is similar to our finding of the price impact of the buy block trades. They show that spreads are at their highest at the open and narrow over the trading day.

The seller initiated block trades show a similar J shaped pattern to those found for the buyer group with price impact being lower at the beginning of the day and at its highest toward the end of the day.

Price impact and trade size

Existing theoretical and empirical research suggests that informed traders submit larger orders than do liquidity traders. If that assumption holds true in the SSM, we expect to have an increasing function relating price impact and order size for both block purchases and sells. To examine how trading activities within different size groups might affect price behaviour, we divide buy and sell block trades into different groups according to trading volume. Following Madhavan and Cheng (1997), we partition block trades into three size categories of (10K - 20K), (20K – 50K) and (greater than 50K).

Table 11: Price Impact and Block Size (Purchases)

VARIABLES	G(1) 10,000-20,000	G(2) 20,000-50,000	G(3) >50,000
% of total	**41%**	**36%**	**23%**
Ln(size)	**0.00112*** **	**0.00156*** **	**0.00220*** **
	(4.98e-05)	(4.64e-05)	(2.72e-05)
Volatility	**0.000767*** **	**0.000827*** **	**0.000602*** **
	(1.63e-05)	(2.07e-05)	(3.31e-05)
Ln(turnover)	**-2.60e-05*** **	**3.69e-05*** **	**0.000539*** **
	(6.17e-06)	(7.45e-06)	(1.10e-05)
Mktreturn	**0.0270*** **	**0.0319*** **	**0.0434*** **
	(0.000506)	(0.000602)	(0.000895)
Momentum	**-0.00110*** **	**-0.00127*** **	**-0.000895*** **
	(5.94e-05)	(6.77e-05)	(9.88e-05)
BAS(effective)	**0.00352*** **	**0.00477*** **	**0.00584*** **
	(3.67e-05)	(4.06e-05)	(4.95e-05)
TimeDum1	**0.000576*** **	**0.000776*** **	**0.00130*** **
	(3.17e-05)	(3.72e-05)	(5.22e-05)
TimeDum2	**-4.84e-05* **	**-0.000159*** **	**-0.000211*** **
	(2.62e-05)	(3.13e-05)	(4.40e-05)
Constant	**-0.00966*** **	**-0.0143*** **	**-0.0203*** **
	(0.000477)	(0.000480)	(0.000319)
Observations	**971,091**	**851,890**	**542,886**
R-squared	0.023	0.033	0.056

Notes: this table lists the estimated coefficients for the cross-section price impact model for the block trade purchases

Price Impact = $\alpha + \beta_1$lnSize + β_2Volatility + $\beta_3$lnTurnover + β_4MarketReturn + β_5Momentum + β_6BAS(effective) + β_7TimeDum1 + β_8TimeDum2 +ε

The Model is run separately for each size category. Block trades are partitioned into three groups. 10k-20k, 20k-50k, and above 50K. The 10k-20k category has the highest number of observations amounting to 41% of the total following by 20k-50k with 36% and finally the over 50k category which has 23% of the total observations. Standard errors in parentheses. *** p<0.01, * p<0.1.

Table 11 presents the price impact coefficients across the different block size categories. All explanatory variables, except TimeDum2, show significant coefficients at the 1% level. Price impact is an increasing function of a trade size, the larger the trade size the greater the price impact. The size coefficient for group 3 is as twice as large as the size coefficient of group 1, suggesting that informed traders prefer larger order sizes which induces higher price impacts. This finding is consistent with the literature. [15]

Volatility has very similar positive coefficients across the different size categories. Turnover as a proxy for liquidity shows negative and significant coefficients in the first group (10k-20k) showing that increasing liquidity reduces the price impact of block trades. However, the signs of the coefficients for the other two groups are positive suggesting a positive relationship between liquidity and price impact. Larger block trades change the perception about the market value of stocks traded, regardless of the liquidity available in the market. The fact that insider trading is not transparent in the SSM and the absence of analyst forecasts seem to have thrown a higher weight onto trading volume as a factor which traders interpret as a strong indication of informed trading.

Market return, as found previously, has a positive relationship with price impact and again the coefficient for the higher volume group is twice that of the lower volume group. The difference in market return coefficients among different size categories, tends to confirm the hypothesis that larger trades tend to be more informative than smaller trades. Block trade purchasers might have some expectation about market wide movements and time their buying accordingly. The negative momentum coefficient shows that block trade purchases carry information and are not just trend following. Block trades in the higher volume category act according to fundamental information rather than positive feedback trading.

The price impact of effective spread (BAS) increases with trade size. The positive continuation of price impact following block trade purchases works as compensation for the higher costs these block trades face. Finally, the intraday time dummies do not show variations in their pattern between different size groups. Block purchases at the beginning of the day always have the greatest price impact.

[15] See for example, Huang and Stoll (1997) and Glosten and Harris (1988).

Table 12: Price Impact and Block Size (Sales)

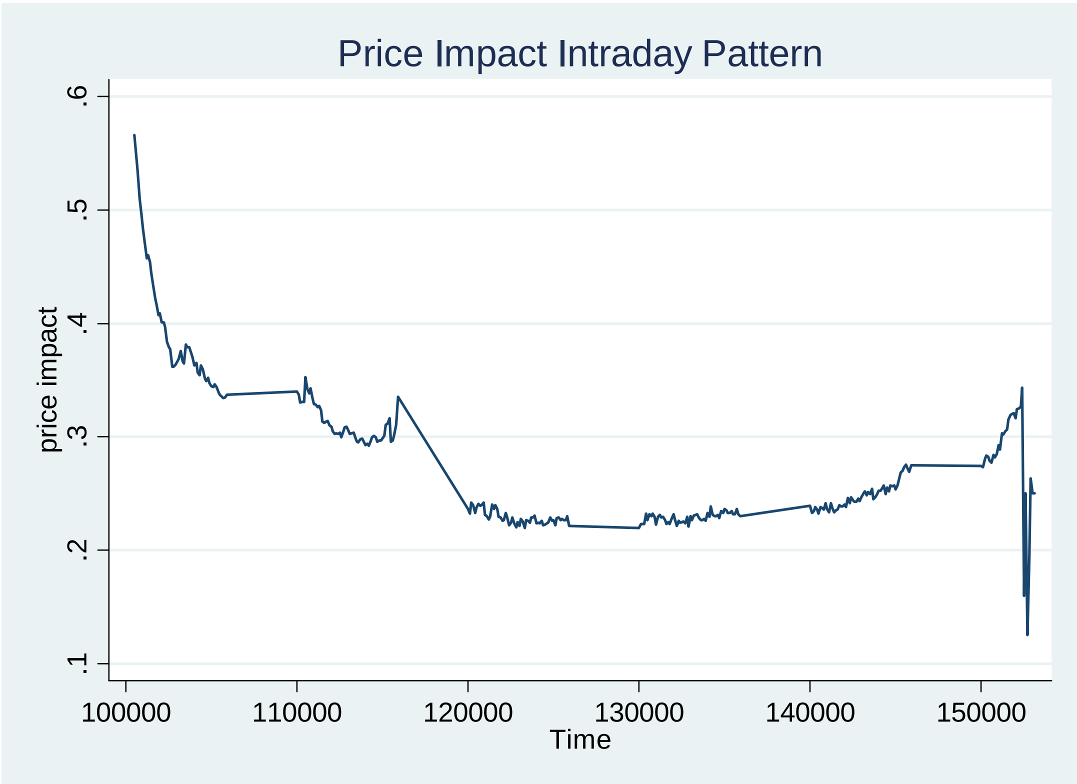
VARIABLES	G(1)	G(2)	G(3)
	10,000-20,000	20,000-50,000	>50,000
% of total	**42%**	**37%**	**21%**
Ln(size)	**-0.000958*** **	**-0.000800*** **	**-2.22e-06**
	(5.76e-05)	(5.42e-05)	(3.73e-05)
Volatility	**-0.000233*** **	**-0.000180*** **	**6.32e-05***
	(1.80e-05)	(2.31e-05)	(3.84e-05)
Ln(turnover)	**-0.000311*** **	**-0.000353*** **	**-0.000292*** **
	(7.05e-06)	(8.61e-06)	(1.33e-05)
Mktreturn	**0.0703*** **	**0.0851*** **	**0.105*** **
	(0.000568)	(0.000678)	(0.00104)
Momentum	**0.000745*** **	**0.000849*** **	**0.000236** **
	(5.99e-05)	(7.26e-05)	(0.000106)
BAS(effective)	**-0.00278*** **	**-0.00397*** **	**-0.00406*** **
	(3.58e-05)	(4.19e-05)	(5.35e-05)
TimeDum1	**-0.000464*** **	**-9.31e-05** **	**0.000586*** **
	(3.65e-05)	(4.33e-05)	(6.41e-05)
TimeDum2	**0.000368*** **	**0.000655*** **	**0.00101*** **
	(3.05e-05)	(3.64e-05)	(5.40e-05)
Constant	**0.00611*** **	**0.00456*** **	**-0.00437*** **
	(0.000551)	(0.000561)	(0.000432)
Observations	**789,197**	**683,068**	**382,807**
R-squared	0.037	0.047	0.047

Notes: this table reports the estimated coefficients for the cross-sectional price impact model for block trades sales. The model is run separately for each size category. Block trades are partitioned into three groups: 10k-20k, 20k-50k and over 50K. The 10k-20k category has the highest number of observations amounting to 42% of the total observations following by 20k-50k with 37% of the total observations and finally the over 50k category which has 21% of the total observations. Standard errors are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 12 shows the regression coefficients for different size groups for block sales. Size has a positive relationship, shown by negative coefficients, with the permanent price impact within the first two size groups. However, the largest size group (over 50k) does not show a statistically significant coefficient. The coefficients for the size variable suggest that small to medium block trades are more informative than larger block trades. This indicates that informed traders might split orders into small and medium orders. Volatility also exhibits intriguing coefficient behaviour, the largest size group has a positive coefficient that is significant at the 10% level. It is assumed that when a stock shows higher volatility we would expect a greater price impact for the risk level that is taken, as observed in the first two size categories. Liquidity (turnover) has a positive relationship with price impact with negative signed coefficients that are significant at the 1% level for all block size categories. The market return coefficient, which is larger for the sell blocks than the buy blocks, suggests that general market movements play an important part in influencing price impact. Higher market returns seem to contribute to the price impact asymmetry between buys and sells as they increase the permanent price effect for the buys and decrease the permanent price effect for the sells.

The behaviours of liquidity, size and momentum in the SSM for block sales among different size groups, suggest that block sales are less information driven than block purchases. Uninformed investors seem to engage in momentum trading for block sales as implied by the positive relationship between the momentum trend and price impact. Moreover, the effect of momentum may be due to a return autocorrelation property. The SSM has two characteristics that might induce returns autocorrelation, which are the prohibition of short selling and the 10% daily cap on price movements. Short selling can be a counterbalancing tool to mitigate the momentum or herding effect. Moreover, limits on prices might create additional "artificial" autocorrelation in stock returns. The intraday time dummy variation supports our finding that small to medium size block trade categories, 10k-20k and 20k-50k, are more informed than the largest group size. Informed trading is highest at the beginning of the day then information is slowly incorporated into prices, until informed trading reaches its lowest point and stays low for the rest of the day. The inverse J-shaped pattern found is similar to that found by Nyholm (2002). This informed trading pattern holds true for the first two categories but not for the last category, over 50k, where the price impact and thus informed trading is at its highest toward the end of the day.

Figure 1: Intraday Variation Pattern of Price Impact



VI. Conclusion

This paper examines the determinants of price impact for block trades in the SSM. As found in the previous literature, we observe a permanent price impact asymmetry between block trade purchases at 0.5% and block trade sales at -0.38%. The price impact of trades is an increasing function of trade volume for block trade purchases, whereas for block trade sales, the price impact does not vary significantly with trade size.

The price impact asymmetry between buyer- and seller-initiated block trades indicates that separate regressions should be run according to the trade sign. We test the price impact in relation to trade sign, trade size, and time of the day. We use various forms of price impacts and spreads in our tests.

Our results suggest that informed traders in the SSM tend to trade large volume with the tendency being higher for block purchases. The number of trades for each trade size group indicates that both buyers and sellers of block trades in the SSM follow similar trading strategies when it comes to splitting orders or "stealth trading".

Price discovery is very rapid in the SSM, the largest portion of the price reaction takes place in the five minutes prior to a block trade execution. On average, the price effect of block trades is small and short-lived. Our findings suggest that resiliency is high in the SSM, price effect is at its highest at the execution, then five trades "minutes" after the block trade has been executed a price reversal is expected. Moreover the price reversal is higher for block sales.

In spite of the unique structure of the SSM; price impact shows similar intraday patterns to those found in the previous literature. For example, information asymmetry is at its highest at the beginning of the day (after the open) then shows a diurnal pattern through the day. The price impact follows an inverse J-shaped intraday pattern.

Finally, informed or sophisticated traders can gain abnormal profits in the SSM through "free riding", a trader can benefit from the overreaction before the block trade and price reversal after the block trade.

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