# Opening and Closing Asymmetry: Empirical Analysis from ISE Xetra

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*Abstract:* Overnight news yields difficulties for price discovery at market opening culminating in additional return volatility. Biais *et al.* (2007) show opening prices are sensitive to order flow from the pre-trading session. We investigate the existence of volatility asymmetry between opening and closing returns and trader over-reaction on the Irish Stock Exchange (ISE). Opening on the ISE follows a non-transparent pre-trading session. We estimate opening returns are 10 per cent more volatile than closing returns. This is significantly smaller compared to other exchanges, such as LSE. The LSE operates under a transparent pre-trading session, which is susceptible to order flow manipulation. We implement an ARMA(1,1) framework to investigate the speed of trader reaction to news. Over-reaction is recorded at the morning auction but is smaller in magnitude when compared to international markets with transparent pre-trading and 'non-binding' orders. The level of price reversal bolsters the over-reaction argument. We estimate a 30 per cent reversal of overnight returns with one third taking place in the first thirty minutes of trading.

## I INTRODUCTION

Determining opening prices in equity markets is a difficult task. Before submitting an order to the opening auction, traders must evaluate any change in the fundamental value of a security due to the possible arrival of

new information during the overnight closure period. Chelley-Steeley(2005) shows this uncertainty leads to trader over reaction resulting in higher return volatility. Biais, Hillion and Spatt (1999) show a transparent pre-trading session can aid information transfer and reduce difficulties in forming opening prices. There are three main structural solutions to the pre-trading phase: (i) a pure call auction (ii) pre-trading with non-binding orders and (iii) pre-trading with binding orders.[1] All three structures are present across European exchanges, however with no consensus on the most efficient.[2]

We examine the return distributions at opening auction on the Irish Stock Exchange (hereafter ISE). This market is an example of a pure call auction market, where the pre-trading session provides no additional information to traders before order submission. Comparisons are drawn to the Kelly (2007) study of SETS on the LSE which operates with a non-binding fully transparent pre-trading session. Non-binding pre-trading has the dis-advantage of traders manipulating prices by creating an order flow that is later cancelled, thus increasing the variance of opening returns. Our data set includes a series of continuous market prices recorded thirty minutes after the opening auction. This provides an estimate of the length and magnitude of any over-reaction at market opening.

As with SETS, accentuated volatility is found at market opening. Comparing opening and closing auctions, the ISE records 10 per cent higher volatility in the morning. This is significantly smaller than SETS average of 47 per cent. Higher volatility following non-binding pre-trading session supports the argument of informed traders using non-binding orders to influence indicative call prices. Interestingly, there is a greater difference (11.5 per cent) between opening returns and continuous trading thirty minutes after the auction.[3] As problems with yielding consensus prices are short lived, this emphasises the importance of a pre-trading session. Moreover, we

[1] A pure call auction may follow a pre-trading session that allows the submission and cancellation of orders but there is no transfer of information regarding order flow. The posted quotes during the session are closing auction prices from the previous day's trading. A non-binding pre-trading session is similar, except for full transparency of the order flow and calculation and dissemination of an indicative call price. A binding order session also has full order flow transparency but does not allow for the cancellation of orders.

[2] The Xetra framework used in Dublin and Frankfurt is an example of a pure call auction. The SETS pre-trading session on the LSE is an example of non-binding fully transparent structure. Examples of a pre-trading phase with binding orders is sparse, some markets (Brazilian Stock Exchange) implement rules about the cancellation of orders, such as orders must be replaced with orders providing greater liquidity. In markets operating with a random finish to pre-trading phase, non-binding orders become binding with some probability.

[3] This is the most conservative estimate of the variance differences. The sample at 8:30 is generated from the last transaction before 8:30 on limit order book. This series includes additional variance created due to the bid ask bounce.

measure the return dispersion around the market return (Relative Risk Dispersion, RRD). The highest dispersion is recorded at the morning auction, with a mean 58 per cent greater than the closing auction. Stivers (1999) shows RRD is an inverse measure of market signal quality, providing an estimate of how difficult it is for traders to interpret new information.

Amihud and Mendelson (1987) provide a partial adjustment model where return volatility can be decomposed in three components: news shocks, trading structure noise and reaction speed of traders to new information (Speed of Adjustment Coefficient, SAC). By calculating returns over 24 hours, news affecting the securities value is equally reflected across the intra-day observations. Since structure noise is identical at the opening and closing, only a differing SAC explains the higher morning volatility. We estimate the SAC using an ARMA(1,1) framework and find over-reaction in the region of 7.5 per cent at the morning auction. This is less than half the size recorded under SETS. This goes in favour of non-binding pre-trading sessions leading to greater over-reaction. There is a steady decline in SAC estimates over the day, with 3 per cent and 1 per cent over-reaction in the continuous market and closing auction respectively. This supports the argument that repeated rounds of trading are required to reduce information noise (see Kyle (1985) and Romer (1993)). The correlation between overnight and day returns yields an estimate of the magnitude of trader over-reaction. A negative correlation is found suggesting a 30 per cent price reversal of any overnight returns. We also estimate 36 per cent of any reversal takes place in the first half hour suggesting immediate correction for over-reaction at the morning auction.

During the period of this study, the ISEQ experienced phenomenal growth outperforming leading international indices for the three years preceding 2007 and is currently attracting record volume.[4] Chelley-Steeley and Lucey (2007) investigate the switch from dealer quotes to order driven price determination on the Irish Stock Exchange. They find no significant change in return distribution pre and post ISE Xetra. However, they do find higher SAC estimates under the order driven system. From Amihud and Mendelson (1987) partial adjustment model, no change in return volatility coupled with an increase in SAC suggests a decrease in structure noise under Xetra. The main focus of their paper was the structure change and opening price determination was not considered. The sample also includes a natural experiment to test market structure under stress: the collapse of the Élan share price in early 2002. Throughout the paper, the 3-month period around the collapse is compared to the general findings of the whole sample.

[4] In 2005/2006 the ISEQ index outperformed Eurostoxx 50, NASDAQ, FTSE 100, CDax and Dow Jones Industrial Average. Average daily turnover for 2007 was €784 million, strongly ahead of the 2006 average of €511 million.

The remaining five sections of this paper are organised as follows. Section II discusses the previous literature. Section III derives the framework of the partial price adjustment model. Empirical analysis and comparison of return distributions is performed in Section IV. The speed of adjustment coefficient and the degree of price reversal is investigated in Section V. Section VI investigates the market opening process under stress (Élan price fall) and Section VII contains the concluding remarks.


## II LITERATURE REVIEW

The opening of equity markets has become synonymous with high return volatility. Surprisingly, the morning action still accounts for a significant proportion of the trading volume implying there must be some advantages to trading.[5] A limit order submitted in an auction setting normally executes at a superior price than that specified, thus creating a excess. The same limit order under continuous trading will execute at a specified price resulting in a smaller payoff for an identical order. (Mendelson, 1982). Madhavan (1992) shows an auction system is more robust to the problems of asymmetric information. Due to the batching of orders, limit orders cannot be picked off in the same fashion as on a limit order book. A trader demanding liquidity avoids the bid-ask spread if they submit a market order to the opening auction. Also, Domowitz and Madhavan (2001) show the auction setting performs well if a security is thinly traded. This is a major problem for large orders submitted under continuous trading as an order will execute at continually worse prices until all of the order is filled.

Initially it was argued the structure in which order matching took place affected the return distribution. Amihud and Mendelson (1987) compare opening and closing returns on the NYSE, with opening returns recording 20 per cent higher volatility. Opening and closing prices where determined under differing structures: a call auction at the open and dealer quotes at the close leading to the initial belief where call auctions exhibit higher volatility. More recently, studies have shown trader reaction to overnight information results in the inflated volatility at the opening. Ronen (2001) investigates a modification to the opening structure on the Tel-Aviv Exchange. Continuous trading rounds preceded the call auction until 1998 when the order of the mechanisms was reversed. This provided a natural experiment to separate the overnight information effect from trading mechanism effect. He finds no

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[5] Amihud and Mendelson (1987) show on average 5.4 per cent of daily volume is recorded at the morning auction, eight times greater than that recorded at the closing auction.

change in the return distribution but cannot reject the null hypothesis of no over-reaction under either opening mechanism. Chelley-Steeley (2005) finds a 25 per cent stronger reaction to news at opening compared to closing for a quote driven sample (pre SETS) on the London Stock Exchange (hereafter LSE). Kelly (2007) shows that the opening and closing volatility asymmetry and difference in trader reaction worsen after the introduction of the order driven market, SETS.

Although above findings show trader over reaction occurs regardless of opening structure, a possible explanation for the difference in magnitude is the pre-trading session. Biais, Bisiere and Pouget (2007) investigate equilibrium discovery and coordination for the three main structural solutions to the pre-trading phase: (i) a pure call auction (ii) pre-trading with non-binding orders and (iii) pre-trading with binding orders. With non-binding orders, after observing attempts to manipulate, traders learn to distrust 'cheap talk' and only coordinate 46 per cent of the time leading to pre-play communication adding very little to price discovery. In contrast, using binding orders generates strong coordination on the equilibrium where players coordinate 85 per cent of the time.

Biais, Hillion and Spatt (1999) investigate if pre-trading aids price discovery at market opening on the Paris Bourse. Early in the pre-trading session, they cannot reject that prices are different from a pure noise sequence. However, nearing the opening action, evidence is consistent with an increase in the informational content and efficiency causing indicative prices to converge to equilibrium market valuations. These findings could be a result of the non-binding nature of the pre-trading orders. Early in the pre-trading session, orders may reflect informed trader attempts to manipulate indicative prices through 'cheap talk' non-binding orders. As opening approaches the execution probability of a 'cheap talk' order increases, as there is a random finish time resulting in greater informational content from the order flow. Brusco, Manzano and Tapia (2003) support this argument when examining trader behaviour in the pre-trading session of the Spanish Stock Exchange. They investigate the evolution of supply and demand elasticities and find trader behaviour is different in the pre-trading phase compared to the open market. Informed traders are found to have no incentive to reveal information and use pre-trading to distort information transfer.

The US equity markets are slower to adopt a pure call auction at opening. The New York Stock Exchange (NYSE) reduces opening over-reaction by restricting the direct submission of public orders in favour of specialists using a non-transparent stabilising auction mechanism. This is similar in nature to a pure call auction ((i) from above) with the exception of no public orders. Madhavan and Panchapagesan (2000) find the current NYSE to be more

efficient than if it was opened under an auction system with public orders. The NASDAQ operates as a dealer quote driven market. The pre-trading phase involves dealers posting non-binding quotes in preparation for market opening. Cao, Ghysels and Hatheway (2000) shows there is strong evidence that the non-binding quotes contain information, significantly aiding price discovery. Ewing (2000) discusses the pressure, placed by the SEC and market participants for the NASDAQ to adopt a call mechanism. NASDAQ after a committee review decided against a pure call auction. Instead they implemented a NASDAQ Official Closing Price (NOCP) in 2003 and a similar system for the opening in 2004, both of which incorporate a limited call auction into the dealer quote system. Bacidore and Lipson (2001) compare securities that have switched from NASDAQ (pre NOCP) to the NYSE reporting lower transaction costs at opening after the switch.

## III  MODEL OF PRICE ADJUSTMENT

Black (1986) decomposed the observed price of a security into two components (i) fundamental value and (ii) noise. Fundamental value is the true unobserved value of a security and the noise represents the difference between the fundamental and observed price. Amihud and Mendelson (1987) first derived a partial adjustment model which makes the distinction between observed and fundamental values of an asset,

$$P_t - P_{t-1} = g(V_t - P_{t-1}) + \mu_t \tag{1}$$

where $P_t$ and $V_t$ are the transaction and fundamental values in logarithms and the coefficient 'g' captures the partial adjustment element. $\mu_t$ is a white noise sequence of pricing errors with mean zero and finite variance, $\sigma^2$. There are two main sources for this noise; noise trading and the trading mechanism. Noise trading is derived from liquidity traders – trading which is unrelated to new information such as portfolio rebalancing or liquidity shocks. Noise from the trading mechanism relates to how much of the return volatility is attributable to the way in which the physical trading takes place. Each trading structure is sensitive to different factors: the ratio of buyers to sellers affects price determination in an auction, the random arrival of buyers and sellers affects the transaction price in a limit order book and dealers' inventory positions are considered in their posted quotes.[6]

[6] Mendelson (1982) discusses the theory of the auction setting and the effect order balance has on price determination. Foucault (1999) looks at the effect of traders arrival rate on the posted limit order quotes. Reiss and Werner (1998) show that dealers trade within pre-defined inventory levels. When a dealer faces extreme inventory positions, posted quotes and inter-dealer trades should be in the direction of a neutral or desired inventory position.

The speed of adjustment coefficient (hereafter SAC), $0 < g < 2$, determines the convergence rate of transaction prices to underlying fundamental values.[7] If 'g' is equal to zero, it implies that prices do not react to a change in the underlying value. A 'g' equal to one corresponds to full although noisy adjustment of transaction prices. When $0 < g < 1$, prices gradually adjust and if $1 < g < 2$ traders over-react to new information. The logarithms of the unobserved fundamental asset value follow a random walk with constant drift,

$$V_t = V_{t-1} + m + e_t \tag{2}$$

where m is a constant drift term, capturing the magnitude of the daily expected return. The noise term, $e_t$, is a white noise term with zero mean and finite variance, $\upsilon^2$. It captures any change in asset value due to the release of new information and is independent of the trading structure. Through induction, one can solve for a securities return variance

$$Var(R_t) = \frac{g}{2-g}\,\upsilon^2 + \frac{g}{2-g}\,\sigma^2 \tag{3}$$

The first term above captures the proportion of the variance explained by variation in the fundamental price, while the second represents the contribution of the structure noise. Return variance is downward biased toward information variance. In the case of full adjustment, the contribution of noise variance is twice that of information variance.[8] This is consistent with the Black (1986) finding of higher volatility in the observed price compared to fundamental value of a security.

The variance of observed returns is positively related to three factors: (i) noise due to market structure and liquidity traders, (ii) new information about the asset's value and (iii) the SAC. The SAC scales the effect of changes in (i) and (ii), escalating variance if there is over-reaction ($1 < g < 2$) leading to $Var(R_t) \geqslant \upsilon^2$. If there is lagged adjustment ($g < 1$), variance is damped yielding $Var(R_t) \leqslant \upsilon^2$ if $\sigma^2 \leqslant \upsilon^2(1-g)$.

Next we consider the first order autocorrelation coefficient,

$$R_{t,\,t-1} = \frac{g(1-g)\upsilon^2 + g\sigma^2}{g\upsilon^2 + 2\sigma^2} = (1-g) - \frac{\sigma^2}{Var(R_t)}$$

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[7] The speed of adjustment ranges $0<g<2$ to ensure prices are finite. See Amihud and Mendelson (1987).

[8] An equal weighting is placed on information variance and noise variance only in the case of extreme over-reaction (g=2).

The autocorrelation between returns reflect two factors: (i) the price adjustment effect, which induces a positive autocorrelation when g < 1 (lagged adjustment case) and a negative autocorrelation when g > 1 (over-reaction case); (ii) the noise effect, which always induces a negative autocorrelation. An autocorrelation of zero occurs when $1 - g$ approaches $\sigma^2 / Var(R_t)$, requiring lagged adjustment equal in magnitude to noise variance. Amihud and Mendelson (1989b) show portfolio diversification removes noise variance, allowing the SAC for portfolios, $g_s$ to be estimated as $1 - \rho_{t,t-1}$. A comparison of g and $g_s$ determines if systematic information transmits faster (slower) than firm specific information.

## IV  EMPIRICAL ANALYSIS – ISE XETRA

### 4.1 *Data and Summary Statistics*

Our empirical investigation compares the return distributions for securities traded on the ISE. The exchanges main index, ISEQ comprises of seventy-five instruments, including a substantial number of preference shares that experience little or no daily turnover. We require securities with a high turnover actively traded across the day resulting in two selection criteria: (i) higher turnover and (ii) a greater number of deals then ISEQ average. Selection based on the number of daily deals avoids the problem of small number of large orders yielding high turnover. Average ISEQ turnover is 2,369.90 million euro with an average of 14,367 transactions. This leads to a sample of fifteen stocks.[9] The study is performed over a five-year period concluding June 2006.[10] The largest stock is AIB, with an average daily turnover of sixty million euro from an average of three hundred transactions.

The trading day can be decomposed into three discrete phases; pre-trading, main trading and post-trading. The pre-trading phase starts each trading day (between 6:30 and 7:50 a.m.) allowing submission of orders but no execution takes place. The posted quotes are the previous day's closing price and no information about order flow is transferred to market participants. The post-trading phase is similar but occurs after the main trading phase, between 4:30 and 5:30, where orders can be submitted and modified. Execution of these orders will not take place until the main trading session the following day. The main trading session is the longest session of the day and the only one where

[9] See appendix 1 (Table A1) for a breakdown of the turnover and number of deals for each individual securities. Previous studies also examine only frequently traded securities, FT30 on LSE (Chelley-Steeley, 2005) and Dow Jones Industrial (Amihud and Mendelson, 1987)

[10] There is one exception to this: C&C was not floated until May 2004. Sample period begins at this time.

execution takes place. It is divided into two auctions and continuous trading.

Continuous trading takes the form of an electronic limit order book. The continuous market is opened with a call auction. There are three stages to an auction. The first is the call stage allowing individuals to submit orders that are aggregated on an order book. The second stage is the price determination process, selecting the auction price that maximises the volume executed at a single price. The last is the clearing phase where orders are matched and cleared off the book. The buy and sell offers closest to the auction price are the starting bid and ask quotes on the limit order book. Continuous trading takes place without interruption until market closing when the above auction is repeated to determine the closing prices.

Each of the returns, $R_{i,t}$ are calculated over a twenty-four hour period,

$$R_{i,t} = P_{i,t} - P_{i,t-1} \qquad i = \text{open, continuous and close.}$$

where $P_i$ is the logarithm of the transaction price at time periods t and t − 1. Information changing the value of the examined securities is equally reflected in returns calculated at the three time periods. Remaining differences in return distributions can be attributed to two sources: (i) differing trading structure noise and (ii) differing SAC. The opening and closing auction operate under a uniform trading system allowing us to separate the overnight information effect from the trading mechanism effect.

Table A2 shows the return variance for each period and the variance ratio statistics – calculated as the opening return variance divided by the continuous and closing return variance respectively. The majority of the variance ratio statistics are greater than unity resulting in 10 per cent greater volatility at opening. Amihud and Mendelson (1987) found similar results for the NYSE, with the opening returns displaying 20 per cent greater variance. This higher volatility could be a result of two factors: trader over-reaction and/or structure noise as NYSE opened and closed under differing structures. Chelley-Steeley (2005) confirmed over-reaction as the cause of excess volatility at opening on the LSE as dealer quotes determined both opening and closing prices. Kelly (2007) investigates the return distributions under SETS on the LSE. This order driven system differs only in the mechanism of the pre-trade phase. Opening returns display 47 per cent higher variance compared to closing returns. The much greater asymmetry can be explained by the price manipulative use of the 'non binding' orders in the pre-trading session.

Also presented in Table A2 is the first order serial correlations, demonstrating the stark changes in return distributions over the day. Amihud and Mendelson (1989a) demonstrate the same factors increasing variance at the opening should also yield greater negativity in first order serial

correlations. The price adjustment effect and the noise effect determine the nature of serial correlation. The serial correlation for opening returns has a tendency to be negative compared to the closing returns that tend to be positive. Difference is not a result of structure noise as a batch auction is used at opening and closing. Differing correlation at opening and closing is consistent with findings from other international equity markets.[11] Although the continuous market records negative correlation, it is significantly smaller than the opening auction. This difference suggests significantly less structure noise and/or a reduction in over-reaction.

From these summary statistics, we can deduce that over-reaction is a feature of the opening process on the ISE. Most likely this is caused by protracted price discovery after the overnight period. The pre-trading phase has a key role in forming consensus value before the opening auction. When we compare the non-transparent pre-trading phase on the ISE with the transparent on the LSE, we find lower volatility asymmetry and which predicts less over-reaction on the ISE.

### 4.2 *Relative Return Dispersion (RRD)*

The previous section analysed time series variance, i.e. the level of dispersion around the expected return of an asset over time. A different measure of security variance is the relative return dispersion, RDD. From Amihud and Mendelson (1989a), RRD measures the dispersion of an individual security return around market return. This provides a dispersion measure not comprising of market wide shocks. Stivers (1999) and Connolly and Wang (2002) show cross-sectional return dispersion to be an inverse measure of the market return signal quality, providing an estimate of the difficulty traders' face interpreting new information.

There are two possible sources of RRD, (i) differing elasticities of individual security prices to that which affects the market as a whole. This alone would result in a constant RRD over the trading day;[12] (ii) idiosyncratic shocks causing deviations of individual security return from the market-induced return. If price discovery is more difficult at market opening, one anticipates a greater RRD at opening compared to closing even after accounting for market wide shocks.

As with time series variance, one can control for news by calculating return over 24 hours, effectively making it constant across the trading day.

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[11] For example, Kelly (2007) shows an average negative correlation of -0.170 at the market opening on SETS.

[12] This assumes the elasticity between securities return and factors affecting the market as a whole, does not change daily.

Any difference in RRD estimates is attributable to noise from the trading structure and/or differences in SAC. RRD is calculated as

$$RRD_{j,t} = \frac{1}{N} \sum_{i=1}^{N} (R^i_{j,t} - R^m_{j,t})^2 \quad j = \text{Open, 8:30 and Close, } N = 15, i = 1,2,....,15$$

where N is the number of firms in the sample. $R^i_{j,t}$ is the log return for the j various structures and $R^m_t$ is the market return at time t. The market return is calculated as the return on the ISEQ at each period. Computing a fifty day moving average for $RRD_{o,t}$ and $RRD_{c,t}$ yields a clear image of the time series behaviour of $RRD_t$ at the opening and closing

$$MA_i = \frac{1}{50} \sum_{s=t-49}^{t} RRD_{i,s} \quad \text{where i = o,c and t > 5}$$

Figure 1: *50 Day Moving Average*
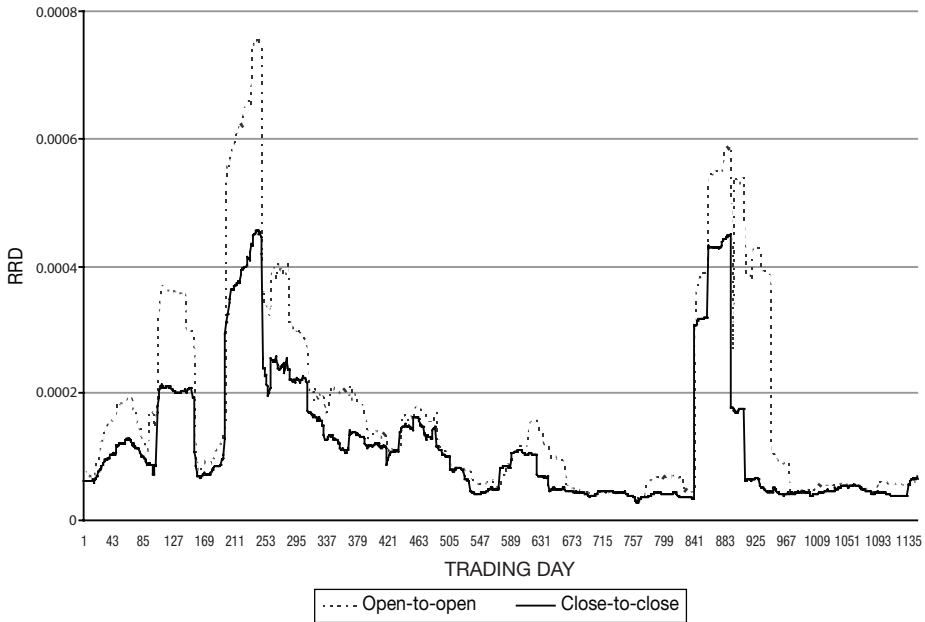


After removing short-term fluctuations, opening auction dispersion is almost consistently greater than the closing auction over the five-year period, with a 51 per cent greater mean than the closing auction. There is significant drop in the RRD by 8:30, where dispersion is 28 per cent greater than closing auction. This supports the argument of over-reaction and repeated trading rounds lowering information noise and hence RRD.

There is a positive relationship between opening and closing asymmetry and dispersion size. From Figure 2, whenever RRD exceeds 0.002, there is a significant increase in the asymmetry between opening and closing estimates. Taking early 2002, (approximately trading day 225) where the Élan price crash yielded excess RRD, the opening auction recorded double the dispersion of the closing auction. The quality of market signal decreases proportionally more at market opening in periods of market stress.

We now perform a test to estimate the difference in RRD at opening and closing conditional on the contemporaneous differences in the aggregate market shocks. We are not concerned with the volatility but instead the differences in RRD between the opening and closing auctions. Our dependent variable is $\Delta RRD = RRD_o - RRD_c$ and a provision is made for the heteroscedastic nature of returns by implementing an ARCH(1) framework.[13] We estimate the model,

$$\Delta RRD_t = \alpha + \beta\big[(R_{o,t}^m)^2 - (R_{c,t}^m)^2\big] + e_t \quad e_t \sim N(0, h_t)$$
$$h_t = a_0 + a_1 e_{t-1}^2$$

where the constant $\alpha$ estimates the difference in level of RRD which is not attributable to market shocks and reflects the noise in price discovery between open and close. $\beta$ captures the relationship between RRD and market-wide shocks. The results below show the unconditional difference in RRD, $\alpha$ is positive and significant and there is support for Amihud and Mendselson (1989a) model with a positive and significant relationship between RRD and systematic shocks.

Table 1: *The Relationship Between Difference in RRD and Market-wide Shocks*
*\*\*denotes significance at 99 per cent confidence*

| $\alpha$ | $\beta$ | $a_0$ | $a_1$ |
|---|---|---|---|
| 0.0000633** | 1.991** | 2.12E-07** | 2.432** |
| (10.775) | (20.181) | (79.862) | (22.903) |

*Notes:* This table shows the results of the regression
$\Delta RRD_t = \alpha + \beta\big[(R_{o,t}^m)^2 + (R_{c,t}^m)^2\big] + e_t \quad e_t \sim N(0, h_t) \quad h_t = a_0 + a_1 e_{t-1}^2$
where $\Delta RRD_t$ is the difference between open-to-open RRD and close-to-close RRD. $(R_{o,t}^m)^2 + (R_{c,t}^m)^2$ is a measure of the difference between market-wide shocks at the opening and closing. $\alpha$, $\beta$, $a_0$ and $a_1$ are the coefficients to be estimated. The t-statistics are given in parenthesis.

[13] For example, see Mandelbrot (1963) and Bollerslev (1986). ARCH errors are detected using Engle (1982) test.

## V  TRADER OVER-REACTION

### 5.1 *Reversal of Overnight Returns*

If there is over-reaction to information disseminated during the overnight period, traders need to correct for these pricing errors.  They must reverse the direction of the price change later in the trading day to converge observed prices back to their fundamental values. The nature of the correlation between overnight and trading day returns will signify if over-reaction followed by reversal has taken place. The empirical investigation of this hypothesis involves calculating the overnight returns,

$$RN_t = P_{o,t} - P_{c,t-1}$$

where $P_{o,t}$ is the log of opening auction price at time t and $P_{c,t-1}$ is the log of price from the previous periods closing auction. Trading day returns are

$$RD_t = P_{c,t} - P_{o,t}$$

where $P_{c,t}$ and $P_{o,t}$ are the log closing and opening prices on the same trading day. If traders "reverse" for over-reaction at the opening auction, the correlation between $RN_t$ and $RD_t$ will be significantly negative,

$$\rho ND = \rho(RN_t, RD_t) < 0$$

From Table A3, estimates show a significant negative correlation between overnight and day returns. The average across securities is –0.297, resulting in one anticipating a 30 per cent reversal of overnight returns. This suggests a strong level of price correction after over-reaction at the opening auction. To capture how much of the reversal takes place directly following the opening auction, we include the opening auction in the overnight period and calculate daily returns starting at 8:30. Evaluating the difference between the correlation coefficients yields an estimate of the reversal taking place in the first thirty minutes of trading. The new correlation coefficients have an average value of –0.190, representing a fall of 36 per cent. This shows an immediate reversal of mis-pricing errors, with over one third of any reversal taking place in the first thirty minutes of trading.

Amihud and Mendelson (1989a) perform a similar study on the Tokyo Stock Exchange and find 6 per cent of overnight returns are reversed during trading. They do not have data from continuous trading to estimate the speed of price reversal. This is consistent with greater volatility asymmetry, (15 per cent on Tokyo compared to 10 per cent on ISE) as price reversal will dampen the twenty-four hour return variance.

The variance difference between overnight and daily returns is noteworthy. The daily variance is significantly greater in fourteen of the fifteen securities with an average variance ratio of 2.102. This is consistent with French and Roll's (1986) result of greater variance for trading compared to non-trading periods. The lack of trader over-reaction and structure noise in non-trading periods is used to explain the difference. It could be argued that this effect is dampened for a small market such as ISE, with the major securities cross-listed on the larger American exchanges. These foreign exchanges operate in the overnight period of the Irish exchange resulting in major announcements and hence more price movement in non-trading periods.[14]

### 5.2 *Estimating the Speed of Adjustment Coefficient*

The unobservable nature of the fundamental asset value makes the estimation of the SAC difficult. Damodaran (1993) first extends the partial price adjustment model to allow for the direct estimation of individual securities' SAC by comparing variances from differing return intervals. There are three weaknesses with this estimation technique: (i) the SAC must converge to one after a set amount of periods (20 days in their case). This does not allow for any under or over reaction in the longer term. (ii) No allowance made for periods of no or thin trading and (iii) estimates do not have a readily derived sampling distribution, yielding problems for significance testing.[15] Theobald and Yallop (2004) show these problems are removed by estimating SAC using the ARMA (1,1) framework. The SAC can be estimated from ARMA (1,1) set-up by re-formulating Equations (1) and (2) into a single equation. Equation (1) is differenced

$$\Delta R_t = g(\Delta V_t - \Delta P_{t-1})_+ \Delta \mu_t$$

substituting for the change in fundamental from Equation (2) yields,

$$\Delta R_t = gm + (1 - g)R_{t-1} + ge_t + \mu_t - \mu_{t-1} \tag{4}$$

equivalently, Equation (4) can be written as an ARMA(1,1) process,

$$R_t = \alpha + \varphi R_{t-1} + \theta \xi_{t-1} + \xi_t$$

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[14] There is some evidence of this, Amihud and Mendelson (1989b) find daily returns volatility for Nikkei 500 securities to be 140 per cent more volatile then overnight returns.
[15] See Theobald and Yallop (2004).

where α is a constant, φ is the auto-regressive coefficient and θ is the coefficient on the composite moving average component. The constant provides an estimate of gm. The price adjustment effect manifests itself in the AR(1) component, with 1 – φ providing a SAC estimate. With full adjustment (φ = 0), returns will be described as a MA(1), only affected by 'noise' resulting from trading structure and liquidity shocks. The problem of thin trading is addressed as it is shown to manifest in higher order moving average terms. Theobald and Yallop (2004) show this ARMA estimator outperforms the interval estimator in terms of root mean squared errors from simulations and has desirable sampling properties for significance testing.

The SAC estimates are displayed in Table A4, showing the greatest reaction is recorded at the morning auction with an average of 7.5 per cent over-reaction to overnight news. Reaction levels decay throughout the trading day, with over-reaction falling to 3 per cent in the continuous market thirty minutes later.  The closing auction records the slowest reaction, which is not significantly different from full adjustment. Decaying trader reaction supports the Kyle (1985) and Romer (1993) argument of repeated trading rounds reducing noise. We calculate the SAC ratios – the opening SAC divided by the continuous and closing SAC's. They indicate clearly the relative speed of adjustment to new information at various periods. Trader reaction is 6 per cent faster when comparing average opening and closing SAC estimates. This is a significant difference but smaller than estimates for large equity markets.

Ozenbas *et al.* (2002) shows protracted price discovery is a feature of the opening process in equity markets culminating in accentuated volatility. This imperfect price discovery process can explain over-reaction at the morning auction. A tendency for over-reaction at the opening is consistent with the findings of Ronen (2001), who examined the opening and closing return distributions on the Tel-Aviv Stock Exchange. He suggests this volatility asymmetry could be a result of institutional barriers specific to the Tel-Aviv exchange. This proved not be to an isolated case with Chelley-Steeley (2005) finding similar volatility asymmetry on the LSE, a former partner market to the ISE. Kelly (2007) investigates return distribution pre and post the introduction of the order driven system, SETS. He shows opening and closing SAC estimates increase culminating greater volatility asymmetry under SETS. Opening SAC estimates are significantly greater compared to those on the ISE, which maybe explained by differences in the pre-trading phase. The lack of potentially price manipulative "non-binding" orders in pre-trading on the SAC results in less information noise and hence smaller over-reaction.

Whereas the opening returns over-react, closing returns are not significantly different from full adjustment. The sample is split, with half displaying over-reaction and half under-reaction, yielding an average over-

reaction of less than 1.5 per cent. Previous studies have shown a tendency for under-reaction at the close. Celley-Steeley (2005) estimates a 11 per cent lagged adjustment for LSE when operating under a quote driven system. Ozenbas *et al.* (2002) argued that price persistence is the consequence of momentum trading. An absence of active trading pressures at the close causes traders to defer order submission until the following morning. This reduces the speed of information transmission encouraging under-reaction. Policy reform included implementing a batch auction at close. Pagano and Schwartz (2003) and Kelly (2007) show a significant increase in price discovery and liquidity at close with the introduction of a closing auction. This is consistent with our findings of full adjustment as the ISE closes under a batch auction.

One must be cautious comparing SAC across the ISE and the LSE as they differ greatly in terms of size. Currently, there is no evidence of the effect of market size on the trader reaction to news. Knif and Pynnonen (1999) and Westermann (2002) show smaller European markets are correlated with the larger markets. They also show the larger markets granger cause the smaller markets. Therefore, the possibility of a lead/lag effect arises in equity markets similar to that of size sorted portfolios (Lo and MacKinley (1990), Jegadeesh and Titman (1995)). If equity markets display a lead/lag effect, one anticipates a higher speed of adjustemnt in the larger markets.[16] Although the morning SAC estimates support the lead/lag argument, the closing estimates do not as both ISE and LSE display full adjustment under the order driven system.

## VI  OPENING AUCTION UNDER STRESS: ÉLAN PRICE FALL EARLY 2002

A main function of market structure is information transfer during periods of major price adjustments. Our sample provides a natural experiment, the fall of the Élan share price. Due to a combination of problems: failed Alzheimer drug trials, accounting practices relating to drug royalties and general investor unrest in global markets, the Élan share price fell 70 per cent, from €50 to €15 in the 3 month period from December 2001 to March 2002. This sub-period represents a time with numerous large news announcements and major re-adjustment of the fundamental share value. We estimate variance, trader over-reaction and price reversal for this period and compare it to Élan estimates over the entire sample period.

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[16] If large market lead small market, then $Cov\{R(L,t-1), R(S,t)\} > Cov\{R(L,t), R(S,t-1)\}$ where $R(L,t)$ and $R(S,t)$ are the returns on large and small markets in period t. Using the cross-covariance relationship developed in Theobald and Yallup (1998), this inequality implies that $g(L) > g(S)$, where $g(L)$ and $g(S)$ are the speeds of adjustment for the large and small markets.

Table 2: *Analysis of the Élan Return Distributions, Price Reversal and SAC Estimates Over the Stock Price Fall. (December 2001 to March 2002). Findings are Compared to a Benchmark of Élan Estimates over the Entire Sample*

|  | *12/2001 – 3/2002* | *Whole Sample* |
|---|---|---|
| *Variance* |  |  |
| $VR_{Open/Close}$ | 1.253 | 1.146 |
| $VR_{Open/8:30}$ | 1.167 | 1.076 |
|  |  |  |
| *Correlation* |  |  |
| $\rho_{Open}$ | −0.036 | 0.027 |
| $\rho_{8:30}$ | −0.010 | 0.011 |
| $\rho_{Close}$ | 0.066 | 0.012 |
|  |  |  |
| *Price Reversal* |  |  |
| $\rho_{Reversal}$ | −0.134 | 0.054 |

Over the entire sample period Élan exhibits large variance asymmetry; with opening returns 14 per cent more volatile than closing returns. There is a considerable increase in volatility asymmetry during the Élan price crash, with opening returns 25 per cent more volatile than closing. Over-reaction to news in the overnight period is the likely explanation. This is particularly pronounced as Élan is cross-listed on the NYSE with numerous news announcements occurring in the overnight period on the ISE. Through the price adjustment effect, trader over-reaction promotes a negative serial correlation. Over the entire sample Élan is one of the few securities displaying positive serial correlation but a negative correlation is recorded at the morning auction over the sub-sample. There is an increase correlation of closing returns implying a greater difference between trader reaction in morning and evening. This is consistent with greater volatility asymmetry.

Figure 2 documents the 5 day MA dispersion around the price crash. It is evident that the revaluation yielded huge spikes in dispersion at all time periods. However, the morning is the worst affected with double the dispersion of that recorded at the closing auction. This shows the relative increase in signal extraction problems at the opening with large shifts in the fundamental value as RRD provides an inverse measure of the difficulties with price discovery.

Large scale price reversal is indicative of traders over-reacting at the opening and correcting for price errors over the trading day. $\rho_{Reversal}$ is estimated as the correlation of overnight to day returns ($\rho_{Reversal}$ in Table A3). The sub-sample estimate is 3.5 times greater than the 5 year Élan estimate, with over 13 per cent of overnight returns reversed. Previously, Élan was the

Figure 2: *Elan Price Crash (12/2001–3/2002) RRD Dispersion*
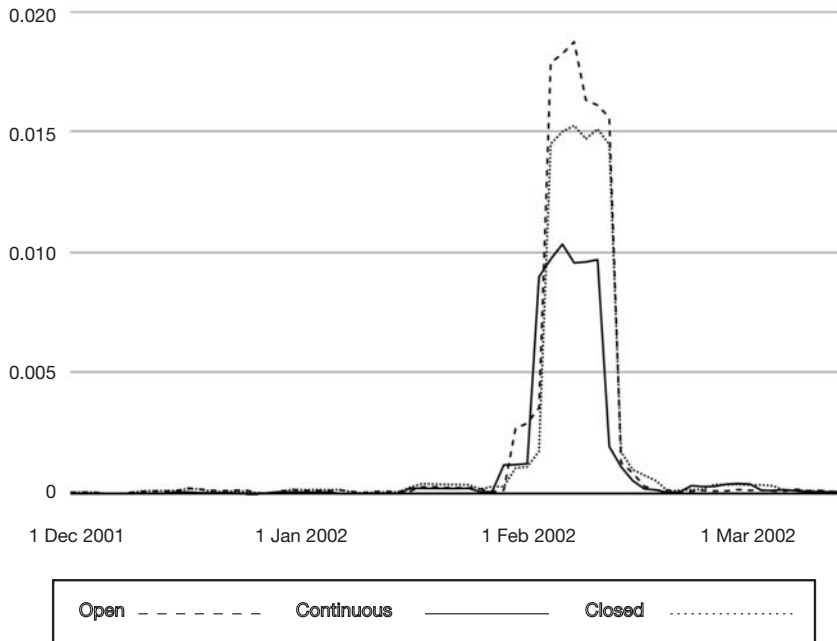


only security not to display reversal of overnight returns. This suggests that over-reaction worsens in periods of major price change. In general, a large proportion (30 per cent) of this reversal takes place in the first thirty minutes of trading. However, $\rho_{Speed}$ shows only 5 per cent of the over-reaction occurs immediately. This suggests in periods of large price movement, correction for over-reaction at the morning auction takes longer.

## VII  CONCLUDING REMARKS

Ozenbas *et al.* (2002) document the difficulties with price discovery at the opening and closing of equity markets resulting in greater return volatility. The absence of order flow at the close was addressed with the implementation of a closing batch auction. The morning auction is a more complex problem. Forming consensus values after the overnight period is difficult causing traders to overreact culminating in a accentuated volatility. Biais, Bisiere and Pouget (2007) show price discovery is heavily influenced by the pre-trading phase. Pre-trading sessions differ in levels of transparency and rules surrounding the cancellation of orders.

We analyse the opening on ISE, where prices are formed following a pre-trading session with a non-transparent order flow. We draw comparisons to the Kelly (2007) study of SETS on the LSE which operates with a non-binding fully transparent pre-trading session. Non-binding pre-trading has the disadvantage of traders manipulating prices by creating an order flow which is later cancelled increasing the variance of opening returns. We find opening returns exhibit 10 per cent greater variance compared to closing returns. Also estimated is the RRD – an inverse measure of the market signal quality. We record 51 per cent greater dispersion in the morning compared to closing, demonstrating the difficultly faced by traders yielding consensus values at the opening auction. This is significantly smaller than LSE where Kelly (2007) finds 47 per cent difference between opening and closing return variance. This suggests that the misuse of the 'non-binding' orders by informed traders in the pre-trading session culminates in higher volatility at the morning auction.

Unique to our data sample is a series of continuous prices recorded thirty minutes after opening. This allows estimation of the duration and size of any over-reaction at market opening. The correlation between overnight and day returns provides an estimate of price reversal. We record a 30 per cent average reversal with one-third taking place in the first thirty minutes of trading. Price reversal of this magnitude is greater than other international markets and partially explains the lower volatility asymmetry found on the ISE. The SAC estimates from the ARMA(1,1) framework support the Romer (1993) argument of repeated trading lowering information noise as over-reaction falls by 5 per cent in the first thirty minutes. An insightful avenue for further research is a true time varying SAC. Currently SAC static estimates are formed at differing intervals but if the SAC was modelled to change for each period, we could determine the full extent and length of the morning over-reaction.

Removal of public orders and/or the use of binding orders are two possible policy changes with the view to improving price discovery at the opening of the ISE. The NYSE dampens opening over-reaction by restricting the direct submission of public orders in favour of specialists using a non-transparent stabilising auction mechanism. Madhavan and Panchapagesan (2000) find the current NYSE to be more efficient than if it was opened under an auction system with public orders. The use of fully binding pre-trade orders is a drastic measure but markets can implement rules, such as large cancellation fees to constrain the ability of traders to revise their orders. In some exchanges, the cancellation of an order can only take place if it is replaced with a new order providing greater liquidity. Biais, Bisiere and Pouget (2007) shows binding orders yield co-ordination among traders and improves price discovery.

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APPENDIX

Table A1: *Sample of Irish Securities Experiencing Greater than Average Volume for the Five Years Ended 30th June 2006, Ranked According to Turnover and Number of Daily Transactions*

| Company | Turnover | No. of Deals |
|---|---|---|
| 1  Allied Irish Banks | 73,886.58 | 373,702 |
| 2  Bank of Ireland | 71,468.56 | 348,880 |
| 3  CRH | 52,212.37 | 241,304 |
| 4  Anglo Irish Bank | 39,842.72 | 197,610 |
| 5  Ryanair Holdings | 32,914.45 | 221,866 |
| 6  Irish Life and Permanent | 24,740.78 | 178,930 |
| 7  Elan | 9,597.94 | 168,002 |
| 8  Kerry Group | 8,437.50 | 105,196 |
| 9  Grafton | 7,384.26 | 75,616 |
| 10  Ind. News and Media | 7,341.45 | 76,476 |
| 11  DCC | 7,134.11 | 68,237 |
| 12  C&C Group | 5,689.76 | 40,342 |
| 13  Paddy Power | 4,088.36 | 42,772 |
| 14  Greencore | 3,858.21 | 64,162 |
| 15  United Drug | 2,395.13 | 33,260 |
| ISEQ Average | 2,369.90 | 14,367 |

Table A2: $\sigma^2$ denotes the Variance of Returns of a Sample of ISE Securities for the Period 1st June 2000 to 31st May 2006. The Centre 2 Columns Present the Variance Ratios; Variance of Opening Returns Divided by Closing and Continuous Return Variance Respectively. This Documents the Magnitude of Variance Asymmetry. $\rho$ is the First Order Serial Correlation Coefficient. The O, 8:30 and a C Subscript Denote Opening, Continuous at 8:30 and Closing Returns Respectively

| Company | $\sigma_O^2$ | $\sigma_{8:30}^2$ | $\sigma_O^2$ | $\sigma_O^2/\sigma_C^2$ | $\sigma_O^2/\sigma_{8:30}^2$ | $\rho_O$ | $\rho_{8:30}$ | $\rho_C$ |
|---|---|---|---|---|---|---|---|---|
| 1 | 0.051 | 0.049 | 0.050 | 1.041 | 1.041 | −0.028 | −0.001 | 0.038 |
| 2 | 0.055 | 0.053 | 0.054 | 1.019 | 1.038 | −0.007 | 0.011 | 0.015 |
| 3 | 0.043 | 0.044 | 0.047 | 0.915 | 0.977 | −0.040 | −0.066 | −0.021 |
| 4 | 0.044 | 0.045 | 0.047 | 0.936 | 0.978 | −0.020 | −0.057 | −0.001 |
| 5 | 0.058 | 0.046 | 0.051 | 1.138 | 1.261 | −0.043 | 0.064 | 0.042 |
| 6 | 0.053 | 0.037 | 0.037 | 1.425 | 1.433 | −0.129* | 0.009 | −0.012 |
| 7 | 1.150 | 1.069 | 1.004 | 1.146 | 1.076 | 0.027 | 0.011 | 0.012 |
| 8 | 0.040 | 0.037 | 0.040 | 1.000 | 1.082 | 0.025 | 0.041 | 0.049 |
| 9 | 0.061 | 0.059 | 0.064 | 0.953 | 1.034 | −0.109 | −0.088 | −0.118 |
| 10 | 0.098 | 0.092 | 0.084 | 1.167 | 1.065 | −0.174* | −0.126 | −0.090 |
| 11 | 0.049 | 0.043 | 0.041 | 1.196 | 1.140 | −0.040 | 0.015 | 0.051 |
| 12 | 0.021 | 0.022 | 0.022 | 0.954 | 0.955 | 0.036 | 0.031 | −0.006 |
| 13 | 0.082 | 0.065 | 0.064 | 1.281 | 1.262 | −0.185* | −0.181* | −0.076 |
| 14 | 0.149 | 0.115 | 0.120 | 1.242 | 1.296 | −0.099* | 0.038 | 0.034 |
| 15 | 0.045 | 0.042 | 0.039 | 1.154 | 1.071 | −0.250* | −0.170* | −0.104 |
| Mean | | | | 1.104 | 1.114 | −0.070 | −0.031 | −0.011 |

Table A3: Variance Ratios and Correlation Coefficients for Overnight (RN) and Daily Returns (RD)

| Company | $\sigma_{RD}^2$ | $\sigma_{RN}^2$ | $\sigma_{RD}^2/\sigma_{RN}^2$ | $\rho_{RD,RN}$ |
|---|---|---|---|---|
| 1 | 0.025 | 0.009 | 2.707 | −0.221 |
| 2 | 0.028 | 0.039 | 0.717 | −0.569 |
| 3 | 0.045 | 0.022 | 2.051 | −0.697 |
| 4 | 0.022 | 0.007 | 3.338 | −0.221 |
| 5 | 0.036 | 0.014 | 2.467 | −0.435 |
| 6 | 0.021 | 0.012 | 1.838 | −0.167 |
| 7 | 0.370 | 0.210 | 1.762 | 0.054 |
| 8 | 0.019 | 0.005 | 3.874 | −0.150 |
| 9 | 0.028 | 0.013 | 2.157 | −0.240 |
| 10 | 0.039 | 0.035 | 1.121 | −0.294 |
| 11 | 0.031 | 0.015 | 2.053 | −0.465 |
| 12 | 0.011 | 0.004 | 2.687 | −0.285 |
| 13 | 0.020 | 0.028 | 0.732 | −0.097 |
| 14 | 0.084 | 0.037 | 2.287 | −0.372 |
| 15 | 0.020 | 0.011 | 1.744 | −0.236 |
| Mean | 0.053 | 0.031 | 2.102 | −0.297 |

Table A4: *Presented is 'g', the Speed of Adjustment Coefficient (SAC) from the Partial Adjustment Model. It is Estimated Through an ARMA(1,1) Framework. The 2 Right Most Columns Present the SAC Ratios and Demonstrate the Relative Speed of Adjustment to New Information at Various Periods. The O, 8:30 and C Subscript Denotes Estimates for Opening, Continuous at 8:30 and Closing Returns Respectively*

| Company | $g_o$ | $g_{8:30}$ | $g_C$ | $g_O/g_C$ | $g_O/g_{8:30}$ |
|---|---|---|---|---|---|
| 1 | 1.044 | 1.003 | 0.958 | 1.090 | 1.041 |
| 2 | 1.011 | 0.990 | 0.986 | 1.025 | 1.021 |
| 3 | 1.042 | 1.070 | 1.024 | 1.018 | 0.974 |
| 4 | 1.043 | 0.936 | 0.957 | 1.090 | 1.114 |
| 5 | 1.057 | 1.020 | 1.001 | 1.056 | 1.036 |
| 6 | 1.130 | 0.991 | 1.008 | 1.121 | 1.140 |
| 7 | 0.973 | 0.989 | 0.988 | 0.985 | 0.984 |
| 8 | 0.975 | 0.957 | 0.949 | 1.027 | 1.019 |
| 9 | 1.119 | 1.129 | 1.095 | 1.022 | 0.991 |
| 10 | 1.174 | 1.130 | 1.091 | 1.076 | 1.039 |
| 11 | 1.042 | 0.985 | 0.950 | 1.097 | 1.058 |
| 12 | 0.965 | 0.969 | 1.006 | 0.959 | 0.996 |
| 13 | 1.196 | 1.192 | 1.082 | 1.105 | 1.003 |
| 14 | 1.102 | 0.954 | 0.965 | 1.142 | 1.155 |
| 15 | 1.263 | 1.187 | 1.117 | 1.131 | 1.064 |
| Mean | 1.076 | 1.033 | 1.011 | 1.063 | 1.042 |