Long-range dependence and transaction initiation

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Abstract

We present empirical evidence that there are periodic daily structural breaks in the trade direction time series process, a fact with implications for several key intra-day characteristics of markets. We suggest that breaks arise as a consequence of daily variation in order flow direction independently of intra-day events and as a consequence of a natural and widespread daily periodicity in the timing of investment decisions. Empirical implementation of our short memory AR model with daily level shifts captures the striking long horizon predictability of trade direction, performs better than the standard long memory ARFIMA alternative and is computationally easier to estimate.

Keywords: trade direction, long memory, structural breaks

JEL: C50, G10

[†]Acknowledgements to be included.

1 Introduction

In this paper we show that key characteristics of financial markets commonly treated as constant should in fact be viewed as changing each day. This is important because it implies that both theoretical microstructure as well as statistical models of intra-day market behaviour need to take such changes into account if they are to deliver reliable conclusions. We focus in particular on showing in detail that the process driving trade direction is subject to daily breaks for an exhaustive cross-section of stocks traded on the London Stock Exchange's electronic order book Stock Exchange Trading System (SETS).

The reason for our focus on the trade direction process is twofold. First, trade direction is a fundamental ingredient of almost all microstructure models (see e.g. Lakonishok, Shleifer, and Vishny 1992, Foucault 1999, Easley, Hvidkjaer, and O'Hara 2002, Chordia, Roll, and Subrahmanyam 2002) which together with the fact that it displays striking time-series predictability even at long horizons makes it of considerable interest in itself. Secondly and relatedly, it is difficult to imagine how changes in this process might arise without corresponding changes in other important intra-day phenomena which are coupled with trade direction. These include market impact and price predictability (related to trade direction predictability via an exact relationship[1]) but also somewhat more subtly, spread size (Huang and Stoll 1997, Bollerslev, Domowitz, and Wang 1997), volatility (Mike and Farmer 2008) and fat tails (Gopikrishnan, Plerou, Gabaix, and Stanley 2000). Examining the evidence for daily changes in the trade direction process is therefore a convenient way to summarily study the evidence that intra-day market dynamics change every day.

[1] In particular, $E_t(\Delta p) = \pi_t m_{t,b} + (1-\pi_t) m_{t,s}$ is the expected price change induced by a trade which is a buy with probability π_t and which has an expected market impact $m_{t,b}$ if it is a buy and $m_{t,s}$ if it is a sell.

The strong predictability of trade direction was first noted at short horizons by Biais, Hillion, and Spatt (1995) while at long horizons it was noted concurrently by Lillo and Farmer (2004) and Bouchaud, Gefen, Potters, and Wyart (2004). In particular the autocorrelation function of trade signs seems to have a large first order autocorrelation of around 50% and has been reported to decay slowly as a power law with an exponent around 0.7 (Lillo, Mike, and Farmer 2005). This suggests strong predictability of trade direction and indeed we report evidence that one-step ahead trade signs can be predicted with 80% accuracy using only the information from the time-series of previous trade signs.[2] Long memory behaviour in other financial variables has attracted a lot of attention since being noted in economic variables by Greene and Fielitz (1977), especially in returns and its powers (Ding, Granger, and Engle 1993, Lobato and Savin 1998), volatility (Beran and Ocker 2001), realized volatility (Corsi 2003) and volume (Lobato and Velasco 2000). Yeo (2006) discusses the difficulties that even short horizon autocorrelations in the direction of limit order submissions pose for market microstructure models, difficulties that are greatly amplified if we consider the *long horizon* predictability of *trade* direction. We will provide evidence that this predictability is mostly an artefact of market conditions that change every day. Microstructure models therefore need not deal with long horizon predictability as long as they are viewed as explaining only a single day with any fixed parameter values.

The main rival approaches to time-series modelling of data with sample autocorrelations that decay approximately as power laws are the use of fractionally integrated processes versus the use of structural breaks. As is well known it is difficult to distinguish between the two even though the economic intuition and statistical properties underlying each representation tends to be very different. In particular, time-series models such as AR or ARMA with structural breaks are usually short memory processes

[2] A similar observation can be found in Gerig (2007, p. 17).

that have misleading sample autocorrelation functions in the sense that their autocorrelations functions behave similarly to power laws in finite samples and for a bounded number of lags (Liu 2000). The distinction between short and long memory processes is important both for the properties of econometric methods and for practical aspects of modelling such as the number of lags that need to be used to produce a forecast.

In terms of interpretation, long memory processes are typically explained using concepts from the natural sciences (long memory having first been observed by Hurst (1951)) while the structural breaks are justified on the basis of the plausible idea of changing conditions (see e.g. Hidalgo and Robinson 1996, Lobato and Savin 1998, Granger and Terasvirta 1999, Diebold and Inoue 2001, Starica and Granger 2005). From a pragmatic empirical perspective, the fractionally integrated process which is the leading long memory process has a convenient parsimonious representation though standard estimators e.g. based on maximising likelihood under normal errors (Sowell 1992) are impractical because they are extremely computationally intensive. On the other hand, structural breaks are easy to incorporate and often very useful in most time-series models (see e.g. Clements and Hendry 1998, 1999), but such models can become unparsimonious and computationally burdensome if the number and dates of breaks are unknown (see e.g. Chen and Tiao 1990, Pesaran, Pettenuzzo, and Timmermann 2006). However, the case of interest here is one in which the number and dates of breaks *are* known and straightforward to interpret and model: we provide evidence that breaks in the trade direction process occur at the start of each trading day and we explain this as the result of the fact that markets are dominated by *daily decisions which are implemented intra-day*. Therefore it is trivial to incorporate structural breaks into standard time-series models even with the computational burden that our massive datasets impose and so we are able to offer characterisations of trade direction that not only perform better than fractionally integrated processes but are also very simple to implement.

Biais, Hillion, and Spatt (1995) offer three explanations for predictability of directional order flow: splitting of orders larger than a typical trade, imitation among traders, or traders reacting similarly to the same event. In a series of papers starting with Lillo, Mike, and Farmer (2005) and conveniently summarized in Bouchaud, Farmer, and Lillo (2008, Section 4), extensive and varied evidence has been provided that the dominant cause of long memory (and therefore trade direction predictability) is order splitting. The models and evidence we present here are in agreement with this, however by exploiting the key additional observation that the time at which most decisions about what orders will be made is at the start of each day (with splitting occurring to execute these orders throughout the day) we are able to develop a new, intuitive and simple model that leads to an analytically tractable and yet very accurate econometric representation of the trade direction process.

Because our models are built on the idea that there is a break in the autocorrelation of trade signs across days, we immediately provide direct evidence for this in Table 1 for data which we describe in detail in Section 3. Our explanation for this break is that most investment decisions occur at the daily level (to be implemented after the open of the next day) with these decisions determining the trade direction imbalance of the next day and causing the apparent long horizon predictability of trade direction. This is consistent with the well known fact that more information arrives between close-to-open than between any other two trades during the trading day so it is natural that decisions to have a greater intensity when most information is received. It is also obviously convenient for investors with even a relatively short investment horizon of over one day (the vast majority) to make a plan for their trading while markets are closed and implement this plan on the next day largely independently of that next day's market activity which is treated as noise in their execution cost. In sum, it seems plausible that daily breaks in time-series properties of order flow (or any variable related to trading behaviour) arise because a significant portion of investment decisions are revised between market close and the next day's open.

In the next Section we introduce our simple behavioural model in which some agents decide the overall size of their desired position at the start of each day and then obtain this position by trading throughout the day, revising their desired position only at the start of the next day. We derive the implications for the trade direction process and in Section 3 we estimate an econometric model that approximates this process comparing it with a fractionally integrated process based on various metrics, both in and out of sample. Some conclusions are presented in Section 4.

2 Daily Effects Autoregressive Model (DEAR)

Our model is based on two different types of investment behavior encapsulated in the following assumption:

Assumption 1 (Trader Types) - *There exist two types of trade initiators in the market:*

(a) 'Fundamentalists', who make decisions to buy or sell on the basis of information available at the start of day t and irrespective of any events unfolding on day t. The proportion π_t of fundamentalist buy volume on day t is an iid random variable from some unknown distribution.

(b) 'Intra-day traders', who trade based on an intra-day signal x_i observed at each trade i so that the probability they buy at trade i is $G(x_i)$ where G is some symmetric sigmoid function (such as logit) with $G(-\infty)=0, G(+\infty)=1$ and $G(0)=0.5$. The intra-day signal is assumed to follow an autoregressive AR(k) process $x_i = b_1 x_{i-1} + ... + b_k x_{i-k} + e_i$ with $E(e_i)=0$ and e_i. $x_0, ..., x_{-k+1}$ and π_t are independent.

(c) The probability that trade i is a fundamentalist trade is a constant α which regulates the intensity of market participation of each type.

The interpretation of fundamentalists here is that of large institutional investors who have made a long-term decision to invest in the asset that will not be perturbed by the changes that occur on a particular day as a consequence of the actions of intra-day traders or their short-term signal x. One interpretation of intra-day traders might be that they exploit minor inefficiencies in the execution strategies of the institutional investors to make profits by taking positions of short duration. The institutional investors determine the overall net direction of trade flow on any day since the intra-day traders will on average buy as often as they sell and with a large number of total trades each day, their net effect will be negligible. Our model abstracts from the behaviour of passive participants in trades (i.e. of limit orders that execute against the fundamentalist or intra-day trade initiators).

Based on this assumption we can establish the following simple proposition:

Proposition 1 (Probability of Buy Trades) *Under A1 the probability that trade i of day t is a buy is given by:*

$$\pi_{i,t} = \alpha\pi_t + (1-\alpha)\, G\left(b_1 x_{i-1,t} + ... + b_k x_{i-k,t} + e_i\right) \tag{1}$$

Proof. Simply note that this probability is the mixture of the probability of buy trades by each type. ■

The qualitative implications of this model are therefore simply that the probability of a buy trade has a level shift each day and otherwise trade direction has short-memory during each day. Denoting $s_{i,t}$ as the sign of trade i on day t with $s_{i,t} = 1$ for a buy and $s_{i,t} = 0$ for a sell, it is easy to see that $Corr\left(s_{i,t}, s_{j,t-l}\right) = 0$ for all $l \neq 0$ and so the time series of trade signs formed by concatenating trades across days cannot have long memory.

As is standard practice in ARFIMA modelling of order direction, we will restrict ourselves to a simple linear probability model framework, approximating (1) with a much more manageable model:

$$\pi_{i,t} = E\left(s_{i,t}|s_{i-1,t},..,s_{0,t},s_{N_{t-1},t-1}...,s_{1,0}\right) = \beta_t + \beta_1 s_{i-1,t} + ... + \beta_k s_{i-k,t}, \qquad (2)$$

where N_t is the total number of trades on day t. We will refer to this as our daily effects autoregressive model (DEAR) where the daily effect appears because β_t changes with t. This model is very similar to the 'random level-shift ARMA' model of Chen and Tiao (1990) though it is simpler because the timing of the level shifts is known and because no MA components are used.

Clearly, DEAR will have the usual drawbacks of linear probability models but estimating (1) by maximum likelihood with samples of our size is unrealistic whereas using a simple panel regression trick estimation of DEAR reduces to estimation by OLS. In particular, β_t can be viewed as a fixed effect in an unbalanced panel data model where each day is a cross-sectional element and each trade i is a time-series element. This means we can easily estimate $\beta_1,...,\beta_k$ by demeaning s_{it} across i for each t (the within transformation) to obtain the demeaned version $s'_{i,t}$ which is then used in a simple OLS regression of $s'_{i,t}$ on $\left(s'_{i-1,t}, s'_{i-2,t},...,s'_{i-k,t}\right)$. From the mean of s_{it} and the estimates of $\beta_1,...,\beta_k$ of the OLS regression it is trivial to obtain an estimate for β_t and this allows us to work with very large numbers of days and trades in each day.[3]

[3]It might seem as an appealing alternative to have a dummy variable corresponding to each daily intercept, but considering the extremely large size of the samples typically used with such models, this would lead to an estimation problem of unmanageable size without special computing infrastructure (over 250 explanatory variables and several hundred thousand observations to work with just one year's trading record for a single stock).

3 Empirical application

3.1 Data Description

We use data from the London Stock Exchange's electronic order book Stock Exchange Trading System (SETS) that includes details of all transactions on all stocks traded in the period 1st August 2005 to 31st July 2006. SETS was at that time and remains one of the most mature electronic order book markets, with high liquidity and a dominant proportion of all traded volume occurring on the electronic order book rather than through competing mechanisms. We chose to focus on an electronic order book market not only because it is now the dominant market design but also because collected and distributed data from these markets typically includes trade direction (as opposed to quote driven markets studied in a previous wave of research where trade direction was inferred with at least some error using the Lee and Ready (1991) algorithm and its refinements - e.g. Finucane (2000)).

We excluded stocks that traded on fewer than 100 days or that had fewer than 100 transactions on any day on which there was a trade. Applying these filters we are left with a sample of 100 highly tradeable stocks closely overlapping with members of the FTSE100 index, whose Reuters Instrument Codes appear in Table 2 together with some descriptive statistics for each stock. According to the LSE, for securities traded at the end of 2002, 65% of their volume was traded on SETS (see LSE 2003) while according to the Fidessa Fragmentation index, 78.2% of the volume of FTSE100 stocks was traded on SETS in December 2008. Further details regarding data format can be found in Lillo and Farmer (2004).

We have repeated the analysis that follows for each stock separately. Because it is difficult to effectively present certain types of result for all stocks (e.g. autocorrelation functions) we first present some results for a single representative stock and then turn to a more exhaustive analysis for all stocks. The chosen representative stock is Astrazeneca (AZN) as it is a highly liquid stock that has also been used as a benchmark in other studies (Lillo and Farmer 2004, Bouchaud, Farmer, and Lillo 2008) and displays behaviour typical with respect to the entire stock universe.

Two thirds of the available days for each stock are used as the in-sample period in which we estimate our DEAR and an ARFIMA model on trade signs. From the remaining days we use the last third of the transactions that occur in each day to evaluate the models out-of-sample, as we need some observations from that day to estimate the day's effect β_t. In particular, we reestimate both models each day using all past data as well as the first 2/3 of the data of the respective day. In this way we obtain an extremely large number of forecasts with modest computational effort. In particular, for AZN we handle a total of 825,041 trades as in sample, and evaluate 108,174 out of sample forecasts (one period ahead) while our entire cross-stock sample contains more than 34 million trades (see Table 2). Since both the DEAR and the ARFIMA models on trade signs are linear probability models we truncate their predictions within [0,1].

3.2 Single stock analysis

Figure 1 (upper subplot) reveals the existence of statistically significant long term autocorrelation in the series extending well beyond five hundred lags. This phenomenon remains robust over each quarter of our sample as shown in Figure 2. The sample autocorrelation function of Figure 1 (bottom subplot) provides visual evidence in favour of a power law decay of the autocorrelation function. It is important to note that the minimum, maximum and median number of trades per day are 724, 7838 and 3133 respectively for Astrazeneca (see Table 2) so even if autocorrelations remain statistically significant beyond a typical day, they are certainly not very economically significant. This is an indication that having parameters that change on a daily basis is reasonable as it ensures that autocorrelations die out roughly around the horizon they actually do. As for any autocorrelation that extends beyond the length of a typical day we believe this is due to the fact that there is some order splitting that occurs over horizons even longer than a day, but this phenomenon is of secondary importance since the autocorrelations over periods longer than a day are very small in terms of economic significance. We are able to detect this phenomenon only because we have an unusually large sample which allows us to observe even very weak effects.

We estimate the order of fractional integration of the series using the spectral regression technique proposed by Geweke and Porter-Hudak (1983). Figure 3 shows various estimates and t-statistics for the null hypothesis of zero order of fractional integration, obtained by gradually increasing the number of lower frequencies included in the regression. The conventional choice for this quantity is the square root of the sample length (alpha=0.5 in the figure), around which we obtain statistically significant estimates of the fractional difference parameter of about 0.2. This evidence is strongly supportive of the presence of long memory within the context of an ARFIMA modelling framework.

Table 3 shows the estimation output of a DEAR(22) specification.[4] The null hypothesis of common intercept (no daily change) is rejected by an F-test. Structural breaks in the intercepts are consistent with the data and the model explains almost 27% of the variability of the series. Figure 4 shows the estimates of the daily intercepts in trade time; it is evident that on several days there exists a statistically significant deviation of β_t from a constant $\beta_t = 0.192$ (this is the value of the intercept that corresponds to an 0.5 buy probability, given the time invariant AR coefficients). In unreported auxiliary results we found no autocorrelation in β_t across days t which motivated the iid component of our assumption A1a.

[4]The order of the model is chosen according to the Schwartz information criterion applied to the in-sample period (the first 2/3 of available days).

The estimation results for an ARFIMA model are presented in detail in Table 3. We estimate the ARFIMA model in two steps; in the first step we estimate the order of fractional integration using the Geweke and Porter-Hudak (1983) spectral regression technique setting the number of included lower frequencies to its conventional choice as mentioned in the previous subsection. Given this estimate, we construct the fractionally differenced series using its infinite autoregressive representation truncated up to an endogenously determined number of lags (491 for AZN). Higher lags appear to have an insignificant impact on the construction of the fractional differenced series since their autoregressive coefficients are smaller than 0.0001 in absolute value. In the second step we estimate an ARMA model using the method of maximum likelihood on the constructed fractionally differenced series with the order of the model chosen according to the Schwartz Information Criterion (SIC).[5]

Figures 5 and 6 show that both the DEAR and the ARFIMA model effectively capture the autocorrelation structure of trade signs over both short and long horizons since their residuals have no visible autocorrelation at any lag.

3.3 All stocks

Having studied the properties of the data and our model in some detail for AZN, we now turn to a coarser analysis for all stocks which suggests the model with short memory and daily breaks is superior to the usual ARFIMA long memory model. Before proceeding with this analysis, note that in Table 4 we present evidence that would usually be taken to suggest long memory. Lillo and Farmer (2004) present an extensive battery of formal statistical tests for long memory on this data and conclude that it is present. By contrast, we argue that long memory is not present and that the reason for this

[5]We estimated all ARMA(p,q) specifications for $p = 0, 1, .., 6$ and $q = 0, 1, .., 6$ and chose the one with the lowest SIC.

results is daily breaks in trade direction the presence of which was directly detected in Table 1.

3.3.1 In sample comparison of DEAR with ARFIMA

Statistics relating to each estimated model for each stock are presented in Table 5. An F-test rejects the null hypothesis that the intercept is the same across days at the 1% level for each stock, effectively rejecting the null of an AR when the alternative is the more general DEAR and highlighting the importance of the daily structural break. DEAR explains on average (across the cross-section of stocks) almost 30% of the variance of trade direction. Similarly, for all stocks the fractional difference coefficient of the ARFIMA model appears statistically significant and therefore we reject the null of a simpler ARMA model against the alternative of an ARFIMA.

On average (across stocks), ARFIMA explains a slightly smaller percentage of trade direction variance than DEAR, but does so with much fewer parameters. For the full cross-section of stocks (100) Ljung-Box Q-tests (reported in Table 6) for up to 10, 20 and 50 lags detected no statistically significant autocorrelation in the residuals from DEAR in 98, 92, 68 stocks, respectively while for ARFIMA the respective quantities are 70, 62 and 56 stocks so DEAR seems superior at capturing autocorrelation patterns. Note that statistical significance here might be too stringent a criterion given the massive samples we use which mean that even very weak effects can be statistically significant; however it is useful as a way of summarizing differences between the two models.

3.3.2 Out of sample performance

We compare the predictive accuracy and bias via the Diebold and Mariano (1995) test on the series of forecast errors from the two models for various forecast horizons. Figure 7 reveals the superiority of DEAR relative to ARFIMA in the majority of stocks, for various loss functions (error, absolute error, square error) and horizons. DEAR performs better almost uniformly across horizons and criteria; an exception might be the one period ahead absolute error but this is statistically insignificant for the majority of stocks (80 out of 100; see Table 7).

DEAR also outperforms ARFIMA in terms of the percentage of correct sign forecasts. The upper subplot of Figure 8 reveals that forecasts from the DEAR model are correct for a larger percentage of trade signs than the ARFIMA model in more than 80 of the 100 stocks and this superiority is maintained across horizons. The mean cross-sectional difference in the percentage of correct trade sign forecasts is more than 2%, as shown in the bottom subplot of the respective figures, especially for horizons of more than 2 periods ahead.

4 Conclusions

Based on considerations of institutional aspects of the timing of investment decisions we have developed a simple econometric model that accurately captures puzzling features of the memory and predictability of trade direction. Contrary to previous research, we suggest using a short-memory model with breaks rather than a long-memory model. This turns out to be effective at capturing the striking autocorrelation properties of trade direction, better according to most metrics than an ARFIMA alternative and is very easy to estimate even with our massive data-sets. The model heavily exploits the idea that autocorrelation patterns in trade signs are driven primarily by daily fluctuations in the proportion of buys and sells which are themselves driven by daily decisions that are largely exogenous to intra-day events. Of course there can be little doubt that some trading decisions span several days or even weeks and hence there is likely to be some autocorrelation of trade signs even across days, however based on the evidence presented here this seems to be of secondary importance relative to daily effects in trade direction.

Given the key role played by trade direction in market microstructure models, the most important implication of these findings is that they suggest a view of markets according to which 'markets change every day'. Researchers attempting to interpret empirical microstructural relationships are advised to consider introducing daily effects in the relationships they analyze while theoretical work might focus on a deeper understanding such changes.

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Liquidity rank (Grouped)		First interval day i																								
		Median of Median Trades Per Day of Stocks in Group					Correlation										z -stat					p-value (null: z = 0)				
							Second interval day i					*Last interval day i-1*														
	Interval (minutes)	*10*	*15*	*30*	*45*	*60*	*10*	*15*	*30*	*45*	*60*	*10*	*15*	*30*	*45*	*60*	*10*	*15*	*30*	*45*	*60*	*10*	*15*	*30*	*45*	*60*
1-10		75.25	105.8	186.8	269.3	347	0.07	0.10	0.17	0.23	0.29	0.03	0.03	0.06	0.08	0.10	1.32	2.45	4.11	5.32	7.07	0.19	0.01	0.00	0.00	0.00
11-20		32	46.75	99.5	147.3	193	0.03	0.07	0.15	0.23	0.25	0.00	0.01	0.04	0.05	0.03	1.07	2.08	3.83	6.48	7.91	0.28	0.04	0.00	0.00	0.00
21-30		13.5	20.5	45.75	77	104.3	0.03	0.05	0.11	0.76	0.81	0.00	-0.02	0.02	-0.01	0.00	0.78	2.26	3.20	35.09	38.93	0.43	0.02	0.00	0.00	0.00
31-40		17	26.25	53	82.25	105.3	0.04	0.02	0.08	0.10	0.77	-0.02	0.00	0.01	0.04	-0.02	2.14	0.70	2.49	2.25	36.05	0.03	0.49	0.01	0.02	0.00
41-50		9	14	31.5	53.5	74.5	0.03	0.03	0.10	0.71	0.75	-0.03	-0.01	0.03	0.06	0.04	1.89	1.30	2.35	29.03	32.38	0.06	0.19	0.02	0.00	0.00
51-60		10	14	33	52.5	73.5	0.03	0.07	0.15	0.20	0.23	0.01	0.02	0.05	0.06	0.06	0.58	1.61	3.49	4.81	6.02	0.56	0.11	0.00	0.00	0.00
61-70		8	12	29	47.5	66	0.05	0.09	0.17	0.23	0.25	-0.01	-0.01	0.03	0.07	0.06	1.90	3.34	4.70	5.72	6.63	0.06	0.00	0.00	0.00	0.00
71-80		7	11.25	26.25	41.5	59.25	0.03	0.05	0.12	0.20	0.25	-0.03	-0.01	0.00	0.03	0.05	2.17	2.02	4.14	5.88	7.25	0.03	0.04	0.00	0.00	0.00
81-90		5	8	18.25	30.75	45.75	0.05	0.03	0.10	0.16	0.20	-0.02	-0.01	0.03	0.03	0.05	2.55	1.26	2.63	4.52	5.11	0.01	0.21	0.01	0.00	0.00
91-100		8.5	12.5	29.5	46	61.5	0.38	0.44	0.57	0.49	0.53	0.45	0.52	0.65	0.70	0.74	-3.04	-3.64	-4.10	-10.82	-11.91	0.00	0.00	0.00	0.00	0.00
1-90		13	19.25	42	65.25	90.75	0.04	0.05	0.12	0.41	0.57	-0.01	0.00	0.03	0.04	0.03	5.15	5.53	9.51	41.08	62.75	0.00	0.00	0.00	0.00	0.00

Table 1: Stocks are grouped according to the number of trades in their sample. Individual stocks' percentages of buy trades per day within the reported interval are stacked to form the group series. We report the median (across stocks of the same group) of the median number of buy trades within the first interval of each day. Subsequent columns show the correlations between the percentage of buy trades within the first and the second interval of the same day as well as between the first interval of the day and the last interval of the previous day. The last two blocks of columns report z-stats and p-values for the null hypothesis of equality between these two correlations for intervals of various lengths.

Stock Name (Code)	# Trades	# Forecasts (1 trade ahead)	# Days	Daily Number of Trades *min*	Daily Number of Trades *max*	Daily Number of Trades *median*	Seconds Between Trades	% Buy Trades	*Stock Name (Code)*	# Trades	# Forecasts (1 trade ahead)	# Days	Daily Number of Trades *min*	Daily Number of Trades *max*	Daily Number of Trades *median*	Seconds Between Trades	% Buy Trades
RDSB	497,008	62,920	199	692	5,045	2,467	12.28	49.57	III	256,055	34,318	242	203	3,300	1,025	29.09	50.18
AZN	825,041	108,174	253	724	7,838	3,133	9.44	49.49	ETI	253,389	34,942	246	288	2,383	978	29.84	50.00
RDSA	286,189	37,436	193	166	3,839	1,486	20.75	48.71	KGF	328,416	40,201	213	121	3,876	1,487	19.90	49.67
BPA	1,135,969	154,445	253	1,031	9,753	4,299	6.86	50.02	SGE	279,461	38,876	253	134	3,222	1,031	27.85	49.89
BLT	925,646	139,085	253	666	9,115	3,492	8.42	50.55	SVT	291,438	40,997	253	181	3,057	1,102	26.73	50.05
RBOS	901,678	112,418	253	696	8,004	3,436	8.64	49.37	IHG	251,814	38,055	217	189	2,994	1,117	26.48	49.65
GSK	894,534	114,331	253	768	6,732	3,473	8.71	49.36	AUN	195,063	24,141	252	222	2,313	700	39.69	50.76
VOD	922,309	112,558	252	1,064	11,824	3,441	8.41	48.38	DXNS	300,724	37,566	253	274	3,078	1,110	25.90	50.61
BARC	751,281	101,020	253	556	6,235	2,792	10.37	49.28	CW.	311,934	33,160	253	151	4,430	1,152	24.98	49.33
LLOY	721,245	83,020	253	565	11,394	2,661	10.80	50.64	CAN	305,522	40,267	195	445	4,547	1,472	19.62	50.00
DGE	601,521	76,450	253	453	4,270	2,315	12.95	51.56	BB.	227,227	32,786	253	128	2,675	827	33.94	49.89
BG.	570,408	79,068	253	389	4,723	2,160	13.66	49.85	PSN	247,792	31,612	230	324	2,508	1,052	28.53	50.21
REED	351,666	42,846	253	303	4,035	1,337	22.16	50.06	TWOD	221,575	31,777	252	217	2,064	818	34.96	49.45
CGNU	541,654	70,499	253	537	5,175	2,020	14.39	50.17	LII	211,820	30,824	253	144	2,365	784	36.74	49.08
TSCO	606,021	74,503	253	597	6,045	2,307	12.86	49.98	ABF	224,584	33,668	253	108	2,474	817	34.53	49.57
XTA	509,193	86,749	225	317	7,877	1,900	13.58	49.64	HMSO	204,121	30,353	233	160	2,449	818	35.08	49.64
BA.	534,284	67,883	253	626	5,456	1,968	14.59	49.48	WPP	248,389	30,198	157	291	4,219	1,525	19.35	49.39
BATS	520,891	65,407	253	407	3,936	1,998	14.96	49.82	SPW	273,350	30,883	198	205	4,391	1,287	22.29	51.49
RTR	442,917	54,570	253	323	7,966	1,656	17.59	50.52	RSA	262,685	34,964	226	411	2,509	1,102	26.48	49.52
STAN	488,996	61,010	253	250	4,955	1,834	15.93	50.34	CNE	218,629	32,285	216	107	2,733	939	30.29	49.40
HBOS	485,937	64,924	193	804	6,235	2,424	12.19	49.07	MRW	258,885	33,302	253	132	3,262	978	30.10	49.59
IMT	420,068	52,166	253	632	3,503	1,606	18.55	49.18	WMH	237,187	30,530	242	205	2,579	890	31.33	49.87
BAY	424,303	56,686	253	436	4,723	1,540	18.35	50.12	GUS	256,973	31,479	157	309	3,792	1,536	18.69	48.71
AZVZ	368,394	49,531	253	242	4,489	1,329	21.14	50.31	EMI	261,522	35,250	253	179	3,535	956	29.72	49.33
ICI	363,132	49,265	253	339	3,904	1,371	21.45	50.02	JMAT	212,562	32,051	253	203	2,086	759	36.60	49.40
CCL	386,353	54,231	220	120	7,062	1,623	17.44	49.96	EMA	234,005	34,676	253	223	4,141	838	33.14	50.13
CBRY	435,115	51,091	253	350	3,661	1,679	17.91	49.20	EZJ	197,881	32,176	253	188	2,583	674	38.94	50.06
NXT	405,805	49,479	253	369	4,318	1,508	19.20	49.16	VED	243,726	51,946	223	177	4,422	781	27.88	50.75
LAND	359,077	52,477	253	443	4,313	1,317	21.68	49.69	FP.	226,345	30,359	253	147	2,954	822	34.39	49.70
GLH	317,645	43,278	253	232	3,237	1,198	24.51	49.12	BOC	266,857	24,778	253	297	5,068	950	29.21	49.07
SMIN	368,663	45,825	253	291	3,995	1,361	21.13	51.05	ARI	171,005	23,456	253	179	1,590	629	45.11	51.37
BSY	409,972	51,801	253	386	4,167	1,545	19.01	49.82	PFG	182,845	23,343	253	179	2,266	675	42.28	50.46
RR.	377,141	51,951	221	437	3,491	1,595	18.03	50.82	ITV	246,914	31,067	229	278	5,581	1,021	28.53	48.95
PRU	408,794	56,030	201	296	6,352	1,931	15.06	49.36	HG	231,949	26,635	180	584	3,645	1,218	23.86	48.85
SSE	336,274	41,497	253	226	2,771	1,297	23.18	50.19	SLOU	182,391	27,694	253	157	2,120	652	42.36	50.60
LOG	224,397	28,372	253	138	3,279	830	34.67	50.11	MSY	190,177	25,094	253	134	2,749	688	40.65	49.85
UU.	352,144	44,262	253	229	2,838	1,346	22.12	50.54	HAS	208,303	27,820	253	154	2,328	767	37.35	50.22
NRK	318,675	41,603	253	170	3,889	1,113	24.42	50.69	SHP	162,770	19,254	116	281	3,370	1,349	21.66	50.72
BT.A	398,578	50,868	209	448	5,879	1,766	16.13	50.04	MAB	163,782	21,869	191	257	2,669	769	35.74	49.50
KEL	263,613	37,858	253	335	2,760	986	29.53	49.95	TNI	160,316	20,956	251	125	1,499	603	47.76	49.61
NPR	312,482	42,475	253	280	2,813	1,155	24.92	50.20	PRTY	192,091	25,812	210	122	6,476	781	33.53	48.51
SBRY	321,253	44,035	251	461	3,463	1,197	24.03	50.04	UBM	146,305	20,269	201	158	1,913	693	41.84	50.71
CPI	266,080	34,979	253	166	3,104	976	29.26	49.76	KESA	155,855	18,756	202	110	3,375	737	39.44	49.29
LMI	290,791	48,009	253	101	3,936	1,031	26.59	49.67	RTO	151,458	18,296	196	137	2,719	753	39.82	48.75
BDEV	258,095	34,024	253	312	2,245	1,006	30.09	49.95	PILK	111,974	7,638	221	111	3,323	437	60.61	47.05
LGEN	331,015	45,201	253	247	3,322	1,223	23.53	49.51	PNN	74,977	9,732	141	107	1,258	478	56.86	48.64
WMPY	237,497	30,794	253	228	2,037	905	32.66	50.74	RB.	375,542	50,463	253	246	3,204	1,382	20.73	12.47
ANTO	227,683	33,614	205	141	3,703	990	27.50	49.01	SN.	243,010	34,144	253	184	3,598	895	32.03	12.34
TATE	278,195	37,492	253	218	3,321	1,002	27.97	50.91	OML	246,524	38,075	253	107	2,531	880	31.53	12.23
YELL	264,641	33,753	246	297	2,955	987	28.57	50.24	CPG	249,659	31,390	253	344	3,610	930	31.20	12.03
mean	345,980	45,821	237	308	4,058	1,367	25.83	48.32	*mean*	345,980	45,821	237	308	4,058	1,367	25.83	48.32
std	195,928	25,938	28	201	1,991	744	10.54	7.43	*std*	195,928	25,938	28	201	1,991	744	10.54	7.43
min	74,977	7,638	116	101	1,258	437	6.86	12.03	*min*	74,977	7,638	116	101	1,258	437	6.86	12.03
max	1,135,969	154,445	253	1,064	11,824	4,299	60.61	51.56	*max*	1,135,969	154,445	253	1,064	11,824	4,299	60.61	51.56

Table 2: Descriptive statistics for the trade direction series for each of the 100 LSE stocks included in our sample.

DEAR(n)				ARFIMA(p,d,q)	
n	Estimate	n	Estimate	First Step: GPH regression	
AR(1)	0.4625*	AR(12)	0.0037*	# frequencies	908 ($\approx \sqrt{T}$)
AR(2)	0.0574*	AR(13)	0.0001*		Estimate
AR(3)	0.0248*	AR(14)	0.0005	d	0.2068*
AR(4)	0.0158*	AR(15)	0.0005	Second Step: ARMA(p,q)	
AR(5)	0.0105*	AR(16)	0.0031*		Estimate
AR(6)	0.0061*	AR(17)	0.0000	const	0.0027*
AR(7)	0.0032*	AR(18)	0.0020	AR(1)	1.4415*
AR(8)	0.0053*	AR(19)	0.0015	AR(2)	-0.4645*
AR(9)	0.0026*	AR(20)	0.0004	MA(1)	-1.1851*
AR(10)	0.0008*	AR(21)	0.0011	MA(2)	0.1891*
AR(11)	0.0038	AR(22)	0.0027*	MA(3)	0.0198*
p-val (H_0 :No daily effects)			0.0000		
# observations (T)			825,041	825,041	
Residual Variance			0.1826	0.1827	
R-square			0.2696	0.2691	

Table 3: AZN - Left panel: Estimates of DEAR(22). Right panel: Two step estimates of ARFIMA(2,0.2,3). Best SIC ARMA orders applied on first two thirds of total days. Star superscripts indicate statistical significance at the 1 percent level.

	Modified Lo (1991) Rescaled Range Statistic, V(q) q							Modified Lo (1991) Rescaled Range Statistic, V(q) q					
Stock Name (Code)	0 *Hurst (1951)*	5	10	default	default q *Andrew's (1991)*	*maximum q for short memory rejection at 1%*	*Stock Name (Code)*	0 *Hurst (1951)*	5	10	default	default q *Andrew's (1991)*	*maximum q for short memory rejection at 1%*
RDSB	8.73	5.25	4.62	3.18	117	>300	III	7.18	4.19	3.66	2.57	100	270
AZN	8.10	4.97	4.43	3.21	133	>300	ETI	9.31	5.43	4.72	3.15	100	>300
RDSA	9.94	6.04	5.37	3.73	96	>300	KGF	10.49	6.12	5.30	3.52	108	>300
BPA	11.37	6.35	5.46	3.62	184	>300	SGE	6.88	4.07	3.55	2.44	100	230
BLT	9.35	5.89	5.26	3.69	128	>300	SVT	6.34	3.68	3.19	2.15	107	120
RBOS	11.18	6.58	5.77	4.03	150	>300	IHG	10.98	6.49	5.65	3.86	96	>300
GSK	7.38	4.28	3.71	2.51	154	>300	AUN	9.74	5.95	5.20	3.58	80	>300
VOD	13.96	7.55	6.25	3.57	172	>300	DXNS	6.53	3.74	3.21	2.01	108	80
BARC	8.55	5.02	4.38	3.06	141	>300	CW.	9.07	5.14	4.38	2.79	112	>300
LLOY	9.27	5.43	4.74	3.19	140	>300	CAN	8.25	4.79	4.15	2.78	106	>300
DGE	6.33	3.70	3.23	2.18	132	160	BB.	4.39	2.69	2.38	1.68	85	20
BG.	9.93	5.84	5.08	3.46	127	>300	PSN	11.88	6.93	6.03	4.04	100	>300
REED	6.12	3.53	3.04	1.94	114	70	TWOD	9.40	5.71	5.03	3.53	86	>300
CGNU	5.49	3.23	2.82	1.92	125	60	LII	6.69	4.05	3.59	2.58	88	230
TSCO	10.44	6.00	5.16	3.26	135	>300	ABF	7.98	4.69	4.08	2.74	94	>300
XTA	7.16	4.47	3.97	2.85	107	>300	HMSO	6.82	4.11	3.62	2.64	87	290
BA.	5.93	3.53	3.09	2.10	120	110	WPP	6.51	3.84	3.34	2.28	95	140
BATS	10.07	5.82	5.05	3.34	130	>300	SPW	6.26	3.76	3.31	2.35	94	190
RTR	5.48	3.27	2.87	2.02	114	80	RSA	10.94	6.27	5.34	3.39	102	>300
STAN	9.45	5.54	4.85	3.37	124	>300	CNE	7.14	4.25	3.75	2.65	93	270
HBOS	13.67	7.95	6.91	4.73	124	>300	MRW	8.27	4.78	4.12	2.65	101	>300
IMT	14.26	8.45	7.42	5.12	115	>300	WMH	15.24	8.93	7.77	5.37	96	>300
BAY	5.96	3.61	3.17	2.19	108	130	GUS	7.89	4.70	4.11	2.85	96	>300
AZVZ	5.96	3.63	3.22	2.25	103	140	EMI	7.01	4.20	3.67	2.52	92	210
ICI	5.78	3.47	3.05	2.17	105	120	JMAT	6.96	4.13	3.62	2.57	92	>300
CCL	10.58	6.39	5.62	3.68	105	>300	EMA	9.01	5.43	4.75	3.44	89	>300
CBRY	5.85	3.39	2.94	1.95	120	70	EZJ	13.36	8.27	7.27	4.98	79	>300
NXT	8.63	5.06	4.41	2.92	115	>300	VED	9.36	6.04	5.37	3.78	77	>300
LAND	8.52	5.02	4.41	3.10	112	>300	FP.	9.73	5.53	4.75	3.11	102	>300
GLH	11.33	6.65	5.79	3.91	106	>300	BOC	7.81	4.60	3.99	2.64	97	>300
SMIN	10.31	6.11	5.34	3.72	109	>300	ARI	6.76	4.13	3.65	2.77	78	280
BSY	7.68	4.52	3.94	2.62	113	>300	PFG	4.94	3.08	2.72	1.93	75	40
RR.	10.64	6.34	5.54	3.84	108	>300	ITV	6.07	3.42	2.90	1.85	104	50
PRU	4.91	2.92	2.55	1.75	112	30	HG	5.96	3.50	3.04	2.04	94	80
SSE	5.77	3.36	2.93	2.05	110	90	SLOU	4.55	2.77	2.45	1.85	81	30
LOG	5.12	3.09	2.72	1.93	87	50	MSY	5.86	3.59	3.16	2.24	79	100
UU.	4.55	2.74	2.40	1.66	104	20	HAS	10.78	6.20	5.29	3.36	95	>300
NRK	6.06	3.61	3.17	2.27	102	160	SHP	6.36	3.85	3.40	2.58	80	290
BT.A	7.51	4.26	3.65	2.37	123	240	MAB	7.99	4.94	4.33	2.98	74	>300
KEL	7.82	4.63	4.03	2.91	97	>300	TNI	4.94	3.04	2.68	1.96	75	40
NPR	7.34	4.29	3.72	2.57	106	>300	PRTY	10.75	6.46	5.58	3.51	82	>300
SBRY	3.96	2.34	2.03	1.39	105	0	UBM	7.83	4.91	4.34	3.19	68	>300
CPI	9.48	5.70	5.00	3.50	94	>300	KESA	5.55	3.43	3.00	2.07	71	60
LMI	8.78	5.43	4.81	3.39	90	>300	RTO	9.87	5.73	4.92	3.13	83	>300
BDEV	8.79	5.28	4.64	3.28	94	>300	PILK	14.01	8.53	7.34	4.77	65	>300
LGEN	8.81	4.93	4.16	2.63	117	>300	PNN	7.92	4.89	4.31	3.15	58	>300
WMPY	8.88	5.32	4.67	3.27	92	>300	RB.	8.70	4.95	4.41	3.88	130	>300
ANTO	8.74	5.26	4.65	3.52	89	>300	SN.	7.91	4.50	3.98	3.29	110	>300
TATE	8.94	5.31	4.64	3.18	99	>300	OML	4.93	2.84	2.51	2.19	106	210
YELL	6.50	3.86	3.37	2.29	96	140	CPG	6.78	3.98	3.56	3.09	101	>300

	0	5	10	default
Short memory Rejected at 5% for # stocks	100	100	100	94
Short memory Rejected at 1% for # stocks	100	100	99	82

Table 4: Long memory tests using Lo's (1991) modified rescaled statistic that takes account of possible autocorrelation of the series up to lag q. Asymptotic critical values at 5 and 1 percent are respectively 1.862 and 2.098. Test statistic reduces towards non-rejection of the null (short memory) as one increases the number of lags. Last column reports the maximum number of lags (up to 300 and rounded) at which the null is rejected.

Stock Name (Code)	*ARFIMA* Fractional Difference Parameter	Standard Error (Asy)	ARMA Order	ARFIMA Error Variance	p-value (H0: No-Daily Intercept)	*DEAR* AR Order	DEAR Error Variance	Error Variance Difference (ARFIMA-DEAR)
RDSB	0.2304	0.0246	(2,2)	0.1767	0.0000	49	0.1766	0.0001
AZN	0.2068	0.0216	(3,2)	0.1827	0.0000	22	0.1826	0.0001
RDSA	0.2201	0.0284	(2,2)	0.1792	0.0000	21	0.1790	0.0002
BPA	0.1862	0.0199	(2,1)	0.1547	0.0000	30	0.1547	0.0001
BLT	0.2339	0.0210	(2,2)	0.1907	0.0000	38	0.1907	0.0000
RBOS	0.2099	0.0211	(3,2)	0.1715	0.0000	20	0.1714	0.0001
GSK	0.1965	0.0212	(4,2)	0.1673	0.0000	80	0.1672	0.0001
VOD	0.1903	0.0210	(3,1)	0.1493	0.0000	54	0.1492	0.0001
BARC	0.1576	0.0222	(5,3)	0.1707	0.0000	24	0.1706	0.0001
LLOY	0.2463	0.0224	(2,4)	0.1699	0.0000	65	0.1698	0.0001
DGE	0.2093	0.0235	(2,1)	0.1700	0.0000	37	0.1699	0.0001
BG.	0.2071	0.0238	(3,4)	0.1723	0.0000	23	0.1721	0.0001
REED	0.1762	0.0269	(1,3)	0.1648	0.0000	50	0.1646	0.0002
CGNU	0.1846	0.0241	(3,2)	0.1721	0.0000	18	0.1719	0.0002
TSCO	0.2151	0.0234	(3,2)	0.1662	0.0000	44	0.1660	0.0003
XTA	0.2574	0.0245	(3,1)	0.1878	0.0000	16	0.1877	0.0001
BA.	0.1841	0.0242	(3,2)	0.1762	0.0000	17	0.1760	0.0002
BATS	0.1828	0.0243	(2,3)	0.1656	0.0000	30	0.1654	0.0002
RTR	0.2340	0.0254	(3,2)	0.1758	0.0000	24	0.1756	0.0002
STAN	0.2788	0.0247	(2,3)	0.1695	0.0000	16	0.1693	0.0002
HBOS	0.2604	0.0248	(2,5)	0.1684	0.0000	15	0.1682	0.0002
IMT	0.2855	0.0257	(3,2)	0.1725	0.0000	18	0.1723	0.0002
BAY	0.2094	0.0257	(2,3)	0.1801	0.0000	21	0.1799	0.0002
AZVZ	0.2189	0.0266	(4,2)	0.1803	0.0000	8	0.1801	0.0001
ICI	0.2159	0.0267	(2,4)	0.1777	0.0000	19	0.1775	0.0002
CCL	0.3154	0.0263	(2,2)	0.1790	0.0000	18	0.1789	0.0001
CBRY	0.2265	0.0255	(3,2)	0.1675	0.0000	27	0.1673	0.0002
NXT	0.3281	0.0260	(2,2)	0.1705	0.0000	28	0.1702	0.0003
LAND	0.2762	0.0268	(3,2)	0.1700	0.0000	19	0.1698	0.0002
GLH	0.2812	0.0277	(2,3)	0.1701	0.0000	13	0.1698	0.0003
SMIN	0.1978	0.0266	(4,2)	0.1737	0.0000	18	0.1734	0.0003
BSY	0.2546	0.0259	(3,2)	0.1723	0.0000	30	0.1721	0.0003
RR.	0.2322	0.0264	(3,2)	0.1758	0.0000	19	0.1754	0.0005
PRU	0.1565	0.0259	(2,5)	0.1745	0.0000	34	0.1743	0.0002
SSE	0.1588	0.0273	(2,1)	0.1689	0.0000	15	0.1687	0.0003
LOG	0.1619	0.0303	(2,1)	0.1798	0.0000	21	0.1794	0.0004
UU.	0.2017	0.0269	(2,1)	0.1771	0.0000	22	0.1768	0.0002
NRK	0.1588	0.0276	(2,4)	0.1751	0.0000	11	0.1749	0.0002
BT.A	0.1707	0.0261	(2,5)	0.1607	0.0000	15	0.1606	0.0001
KEL	0.2101	0.0290	(3,2)	0.1743	0.0000	12	0.1737	0.0006
NPR	0.2352	0.0278	(1,2)	0.1698	0.0000	29	0.1695	0.0004
SBRY	0.1346	0.0276	(2,1)	0.1727	0.0000	31	0.1724	0.0003
CPI	0.2738	0.0290	(3,2)	0.1775	0.0000	20	0.1771	0.0003
LMI	0.3045	0.0283	(2,2)	0.1862	0.0000	12	0.1858	0.0003
BDEV	0.2444	0.0292	(5,1)	0.1770	0.0000	13	0.1767	0.0004
LGEN	0.1204	0.0274	(2,1)	0.1580	0.0000	27	0.1579	0.0002
WMPY	0.3199	0.0298	(3,2)	0.1763	0.0000	7	0.1758	0.0004
ANTO	0.3064	0.0301	(2,2)	0.1779	0.0000	6	0.1775	0.0004
TATE	0.1842	0.0286	(3,2)	0.1739	0.0000	31	0.1735	0.0005
YELL	0.2357	0.0290	(5,1)	0.1752	0.0000	13	0.1749	0.0003
III	0.2322	0.0292	(2,3)	0.1685	0.0000	13	0.1681	0.0003
ETI	0.2639	0.0293	(2,3)	0.1683	0.0000	17	0.1679	0.0004
KGF	0.2820	0.0274	(2,3)	0.1690	0.0000	16	0.1687	0.0003

Table 5a: Estimation results of DEAR and ARFIMA models fitted to the trade signs of our 100 selected LSE stocks.

	ARFIMA				DEAR			
Stock Name (Code)	***Fractional Difference Parameter***	***Standard Error (Asy)***	***ARMA Order***	***ARFIMA Error Variance***	***p-value (H0: No-Daily Intercept)***	***AR Order***	***DEAR Error Variance***	***Error Variance Difference (ARFIMA-DEAR)***
SGE	0.1889	0.0286	(2,3)	0.1726	0.0000	18	0.1723	0.0003
SVT	0.1404	0.0283	(2,2)	0.1662	0.0000	19	0.1659	0.0003
IHG	0.2475	0.0294	(2,2)	0.1729	0.0000	26	0.1726	0.0003
AUN	0.2520	0.0314	(1,2)	0.1841	0.0000	18	0.1836	0.0005
DXNS	0.2037	0.0281	(3,2)	0.1647	0.0000	31	0.1644	0.0004
CW.	0.0876	0.0278	(3,2)	0.1619	0.0000	20	0.1617	0.0002
CAN	0.2042	0.0279	(4,2)	0.1681	0.0000	22	0.1679	0.0002
BB.	0.1712	0.0302	(1,2)	0.1838	0.0000	27	0.1834	0.0004
PSN	0.2915	0.0295	(2,2)	0.1678	0.0000	19	0.1675	0.0003
TWOD	0.2250	0.0304	(2,2)	0.1807	0.0000	10	0.1802	0.0004
LII	0.2637	0.0307	(5,2)	0.1773	0.0000	10	0.1768	0.0004
ABF	0.2244	0.0303	(1,1)	0.1711	0.0000	17	0.1707	0.0004
HMSO	0.2305	0.0310	(2,3)	0.1775	0.0000	20	0.1771	0.0004
WPP	0.2145	0.0295	(1,1)	0.1732	0.0000	22	0.1729	0.0002
SPW	0.1729	0.0288	(3,2)	0.1788	0.0000	27	0.1785	0.0003
RSA	0.1832	0.0291	(2,1)	0.1656	0.0000	25	0.1653	0.0003
CNE	0.2460	0.0305	(2,2)	0.1721	0.0000	12	0.1716	0.0005
MRW	0.2282	0.0292	(3,2)	0.1674	0.0000	26	0.1670	0.0004
WMH	0.2601	0.0298	(2,5)	0.1704	0.0000	14	0.1700	0.0004
GUS	0.2016	0.0292	(2,1)	0.1744	0.0000	36	0.1741	0.0003
EMI	0.2299	0.0291	(2,2)	0.1786	0.0000	16	0.1783	0.0004
JMAT	0.1874	0.0307	(3,0)	0.1727	0.0000	11	0.1723	0.0004
EMA	0.2862	0.0299	(3,2)	0.1793	0.0000	20	0.1786	0.0007
EZJ	0.2968	0.0313	(2,1)	0.1858	0.0000	27	0.1852	0.0006
VED	0.2926	0.0296	(3,1)	0.1966	0.0000	20	0.1962	0.0004
FP.	0.2137	0.0302	(2,1)	0.1611	0.0000	24	0.1607	0.0004
BOC	0.1558	0.0289	(2,1)	0.1732	0.0000	15	0.1729	0.0003
ARI	0.2583	0.0325	(3,2)	0.1824	0.0000	8	0.1818	0.0006
PFG	0.2181	0.0319	(3,1)	0.1889	0.0000	18	0.1882	0.0007
ITV	0.1519	0.0295	(2,1)	0.1606	0.0000	22	0.1604	0.0002
HG	0.1720	0.0300	(1,2)	0.1713	0.0000	27	0.1710	0.0002
SLOU	0.1698	0.0319	(3,2)	0.1805	0.0000	7	0.1801	0.0004
MSY	0.2570	0.0316	(4,1)	0.1839	0.0000	20	0.1835	0.0005
HAS	0.1894	0.0309	(2,1)	0.1658	0.0000	13	0.1655	0.0003
SHP	0.1788	0.0329	(2,1)	0.1780	0.0000	22	0.1778	0.0002
MAB	0.2757	0.0329	(2,2)	0.1863	0.0000	16	0.1859	0.0005
TNI	0.1792	0.0330	(1,1)	0.1849	0.0000	11	0.1843	0.0006
PRTY	0.3411	0.0315	(2,2)	0.1793	0.0000	22	0.1789	0.0004
UBM	0.1988	0.0338	(1,1)	0.1910	0.0000	21	0.1904	0.0006
KESA	0.2283	0.0333	(2,0)	0.1875	0.0000	24	0.1870	0.0005
RTO	0.1672	0.0335	(1,2)	0.1682	0.0000	26	0.1677	0.0005
PILK	0.3130	0.0363	(1,1)	0.1830	0.0000	14	0.1822	0.0008
PNN	0.3094	0.0404	(3,1)	0.1847	0.0000	16	0.1841	0.0006
RB.	0.0894	0.0265	(5,2)	0.0671	0.0000	23	0.0671	0.0001
SN.	0.0659	0.0297	(4,3)	0.0678	0.0000	5	0.0677	0.0001
OML	0.0648	0.0295	(5,3)	0.0695	0.0026	5	0.0694	0.0001
CPG	0.1210	0.0294	(3,2)	0.0710	0.0000	4	0.0709	0.0001
mean	0.2171	0.0282		0.1700	0.0000	22	0.1697	0.0003
std	0.0566	0.0034		0.0222	0.0003	12	0.0222	0.0002
min	0.0648	0.0199		0.0671	0.0000	4	0.0671	0.0000
max	0.3411	0.0404		0.1966	0.0026	80	0.1962	0.0008

Table 5b: Continuation of previous subtable.

	Q-test p -value (H0: No autocorrelation up to lag k)								
	k = 10			k = 20			k = 50		
Stock Name (Code)	***Order Signs***	***ARFIMA Residuals***	***DEAR Residuals***	***Order Signs***	***ARFIMA Residuals***	***DEAR Residuals***	***Order Signs***	***ARFIMA Residuals***	***DEAR Residuals***
RDSB	0.00	0.19	1.00	0.00	0.47	1.00	0.00	0.53	1.00
AZN	0.00	0.87	1.00	0.00	0.76	1.00	0.00	0.24	0.05
RDSA	0.00	0.35	1.00	0.00	0.53	1.00	0.00	0.79	0.00
BPA	0.00	0.04	1.00	0.00	0.00	1.00	0.00	0.00	0.80
BLT	0.00	0.06	1.00	0.00	0.40	1.00	0.00	0.41	0.08
RBOS	0.00	0.72	1.00	0.00	0.88	1.00	0.00	0.68	0.53
GSK	0.00	1.00	1.00	0.00	1.00	1.00	0.00	0.92	1.00
VOD	0.00	0.06	1.00	0.00	0.02	1.00	0.00	0.00	1.00
BARC	0.00	0.97	1.00	0.00	0.73	1.00	0.00	0.75	0.16
LLOY	0.00	0.89	1.00	0.00	0.85	1.00	0.00	0.13	1.00
DGE	0.00	0.76	1.00	0.00	0.00	1.00	0.00	0.00	0.89
BG.	0.00	0.21	1.00	0.00	0.31	1.00	0.00	0.40	0.66
REED	0.00	0.92	1.00	0.00	0.75	1.00	0.00	0.78	1.00
CGNU	0.00	0.01	1.00	0.00	0.00	1.00	0.00	0.00	0.00
TSCO	0.00	0.00	1.00	0.00	0.00	1.00	0.00	0.00	1.00
XTA	0.00	0.00	1.00	0.00	0.00	1.00	0.00	0.02	0.00
BA.	0.00	0.15	1.00	0.00	0.00	1.00	0.00	0.00	0.00
BATS	0.00	0.20	1.00	0.00	0.25	1.00	0.00	0.09	0.88
RTR	0.00	0.88	1.00	0.00	0.72	1.00	0.00	0.62	0.55
STAN	0.00	0.13	1.00	0.00	0.01	1.00	0.00	0.03	0.26
HBOS	0.00	0.77	1.00	0.00	0.93	0.97	0.00	0.88	0.02
IMT	0.00	0.75	1.00	0.00	0.91	1.00	0.00	0.91	0.13
BAY	0.00	0.94	1.00	0.00	0.67	1.00	0.00	0.97	0.30
AZVZ	0.00	0.39	0.01	0.00	0.50	0.00	0.00	0.75	0.00
ICI	0.00	0.92	1.00	0.00	0.27	1.00	0.00	0.04	0.16
CCL	0.00	0.16	1.00	0.00	0.40	1.00	0.00	0.33	0.00
CBRY	0.00	0.16	1.00	0.00	0.29	1.00	0.00	0.39	0.94
NXT	0.00	0.15	1.00	0.00	0.37	1.00	0.00	0.70	1.00
LAND	0.00	0.97	1.00	0.00	1.00	1.00	0.00	0.94	0.29
GLH	0.00	0.84	1.00	0.00	0.66	0.58	0.00	0.53	0.13
SMIN	0.00	0.00	1.00	0.00	0.00	1.00	0.00	0.00	0.56
BSY	0.00	0.03	1.00	0.00	0.05	1.00	0.00	0.03	0.95
RR.	0.00	0.00	1.00	0.00	0.00	1.00	0.00	0.00	0.37
PRU	0.00	1.00	1.00	0.00	0.00	1.00	0.00	0.00	0.97
SSE	0.00	0.19	1.00	0.00	0.00	0.99	0.00	0.00	0.06
LOG	0.00	0.54	1.00	0.00	0.41	1.00	0.00	0.72	0.88
UU.	0.00	0.99	1.00	0.00	0.14	1.00	0.00	0.02	0.00
NRK	0.00	0.80	1.00	0.00	0.71	0.11	0.00	0.72	0.00
BT.A	0.00	0.84	1.00	0.00	0.90	0.87	0.00	0.96	0.00
KEL	0.00	0.00	1.00	0.00	0.00	0.60	0.00	0.00	0.36
NPR	0.00	0.03	1.00	0.00	0.00	1.00	0.00	0.00	1.00
SBRY	0.00	0.01	1.00	0.00	0.00	1.00	0.00	0.00	0.96
CPI	0.00	0.93	1.00	0.00	0.68	1.00	0.00	0.12	0.34
LMI	0.00	0.43	1.00	0.00	0.48	0.35	0.00	0.60	0.00
BDEV	0.00	0.96	1.00	0.00	0.80	1.00	0.00	0.33	0.26
LGEN	0.00	0.16	1.00	0.00	0.45	1.00	0.00	0.01	0.10
WMPY	0.00	0.43	0.19	0.00	0.43	0.01	0.00	0.47	0.02
ANTO	0.00	0.00	0.06	0.00	0.00	0.11	0.00	0.02	0.13
TATE	0.00	0.00	1.00	0.00	0.00	1.00	0.00	0.00	1.00
YELL	0.00	0.87	1.00	0.00	0.78	0.79	0.00	0.81	0.00
III	0.00	0.22	1.00	0.00	0.16	0.99	0.00	0.23	0.57
ETI	0.00	0.17	1.00	0.00	0.13	1.00	0.00	0.40	0.45
KGF	0.00	0.04	1.00	0.00	0.00	0.94	0.00	0.00	0.00
SGE	0.00	0.09	1.00	0.00	0.00	1.00	0.00	0.00	0.00
SVT	0.00	0.11	1.00	0.00	0.10	1.00	0.00	0.07	0.09
IHG	0.00	0.79	1.00	0.00	0.81	1.00	0.00	0.48	0.96
AUN	0.00	0.02	1.00	0.00	0.00	1.00	0.00	0.00	0.92
DXNS	0.00	0.00	1.00	0.00	0.00	1.00	0.00	0.00	0.55
CW.	0.00	0.84	1.00	0.00	0.61	1.00	0.00	0.78	0.01

Table 6a: Ljung-Box Q test on the trade sign time series as well as on the residuals of DEAR and ARFIMA models. The test is repeated for k=10,20 and 50 lags of the trade signs.

Stock Name (Code)	k = 10 Order Signs	k = 10 ARFIMA Residuals	k = 10 DEAR Residuals	k = 20 Order Signs	k = 20 ARFIMA Residuals	k = 20 DEAR Residuals	k = 50 Order Signs	k = 50 ARFIMA Residuals	k = 50 DEAR Residuals
	Q-test p -value (H0: No autocorrelation up to lag k)								
CAN	0.00	0.34	1.00	0.00	0.21	1.00	0.00	0.08	0.23
BB.	0.00	0.70	1.00	0.00	0.22	1.00	0.00	0.12	0.81
PSN	0.00	0.41	1.00	0.00	0.26	1.00	0.00	0.05	0.24
TWOD	0.00	0.33	1.00	0.00	0.20	0.74	0.00	0.23	0.06
LII	0.00	0.99	1.00	0.00	0.58	0.54	0.00	0.33	0.01
ABF	0.00	0.00	1.00	0.00	0.00	1.00	0.00	0.00	0.98
HMSO	0.00	0.57	1.00	0.00	0.60	1.00	0.00	0.65	0.99
WPP	0.00	0.01	1.00	0.00	0.00	1.00	0.00	0.00	0.00
SPW	0.00	0.12	1.00	0.00	0.35	1.00	0.00	0.22	0.67
RSA	0.00	0.66	1.00	0.00	0.00	1.00	0.00	0.00	0.26
CNE	0.00	0.00	1.00	0.00	0.00	1.00	0.00	0.00	0.12
MRW	0.00	0.02	1.00	0.00	0.00	1.00	0.00	0.00	0.74
WMH	0.00	0.96	1.00	0.00	0.48	1.00	0.00	0.51	0.85
GUS	0.00	0.00	1.00	0.00	0.00	1.00	0.00	0.00	1.00
EMI	0.00	0.08	1.00	0.00	0.11	1.00	0.00	0.11	0.19
JMAT	0.00	0.22	1.00	0.00	0.01	0.08	0.00	0.00	0.00
EMA	0.00	0.00	1.00	0.00	0.00	1.00	0.00	0.00	0.97
EZJ	0.00	0.02	1.00	0.00	0.07	1.00	0.00	0.13	1.00
VED	0.00	0.33	1.00	0.00	0.51	1.00	0.00	0.23	0.05
FP.	0.00	0.29	1.00	0.00	0.04	1.00	0.00	0.05	0.82
BOC	0.00	0.52	1.00	0.00	0.25	0.43	0.00	0.46	0.00
ARI	0.00	0.82	1.00	0.00	0.90	0.99	0.00	0.96	0.98
PFG	0.00	0.00	1.00	0.00	0.00	1.00	0.00	0.00	0.68
ITV	0.00	0.36	1.00	0.00	0.23	1.00	0.00	0.48	0.14
HG	0.00	0.18	1.00	0.00	0.00	1.00	0.00	0.04	0.66
SLOU	0.00	0.92	0.49	0.00	0.50	0.06	0.00	0.69	0.13
MSY	0.00	0.76	1.00	0.00	0.63	1.00	0.00	0.27	0.72
HAS	0.00	0.62	1.00	0.00	0.26	0.02	0.00	0.12	0.00
SHP	0.00	0.73	1.00	0.00	0.86	1.00	0.00	0.41	1.00
MAB	0.00	0.71	1.00	0.00	0.76	1.00	0.00	0.80	0.03
TNI	0.00	0.00	1.00	0.00	0.00	0.78	0.00	0.00	0.28
PRTY	0.00	0.70	1.00	0.00	0.60	1.00	0.00	0.93	0.32
UBM	0.00	0.01	1.00	0.00	0.00	1.00	0.00	0.00	0.27
KESA	0.00	0.34	1.00	0.00	0.10	1.00	0.00	0.05	0.98
RTO	0.00	0.88	1.00	0.00	0.41	1.00	0.00	0.41	0.83
PILK	0.00	0.87	1.00	0.00	0.92	0.92	0.00	0.99	0.72
PNN	0.00	0.97	1.00	0.00	0.94	1.00	0.00	0.88	0.99
RB.	0.00	0.95	1.00	0.00	0.69	1.00	0.00	0.79	0.20
SN.	0.00	0.60	1.00	0.00	0.87	0.00	0.00	0.83	0.00
OML	0.00	1.00	0.70	0.00	1.00	0.00	0.00	0.81	0.00
CPG	0.00	0.00	0.33	0.00	0.00	0.00	0.00	0.00	0.00
mean	0.00	0.43	0.96	0.00	0.35	0.87	0.00	0.32	0.44
std	0.00	0.38	0.18	0.00	0.34	0.30	0.00	0.34	0.40
min	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00
max	0.00	1.00	1.00	0.00	1.00	1.00	0.00	0.99	1.00

Table 6b: Continuation of previous subtable.

Stock Name (Code)	**Loss Function: Error. Periods Ahead:**						**Loss Function: Absolute Error. Periods Ahead:**						**Loss Function: Square Error. Periods Ahead:**					
	1	**3**	**5**	**10**	**20**	**50**	**1**	**3**	**5**	**10**	**20**	**50**	**1**	**3**	**5**	**10**	**20**	**50**
RDSB	5.8	4.3	4.1	1.5	-0.8	-1.8	-1.2	14.8	-2.5	-1.3	0.7	3.0	3.6	62.3	50.9	65.8	92.9	146.0
AZN	5.7	3.6	0.6	-2.9	-5.0	-3.9	0.8	6.8	-12.5	-5.2	1.5	2.5	7.5	96.6	84.0	114.5	192.7	214.9
RDSA	5.3	3.1	2.9	-0.3	-2.4	-3.8	-1.0	12.3	-1.3	-0.4	2.5	1.0	4.1	64.1	48.1	64.0	86.4	99.8
BPA	5.2	5.0	4.9	4.7	4.5	4.1	-4.3	36.5	22.6	6.3	1.7	-3.7	3.3	82.6	50.0	15.4	5.3	-3.3
BLT	6.7	6.0	6.0	4.1	2.0	1.2	-1.5	27.5	4.3	0.1	1.0	1.7	4.5	106.3	90.7	116.9	164.8	247.6
RBOS	7.8	5.6	3.2	1.3	-1.2	-2.8	-0.9	3.9	-15.7	-7.1	-0.2	3.7	5.7	89.1	82.6	120.9	179.7	235.3
GSK	5.9	2.7	0.6	-2.7	-4.9	-4.7	0.6	-7.5	-21.3	-11.5	1.4	5.8	5.7	75.6	81.1	92.6	200.1	273.5
VOD	4.1	3.6	3.5	3.2	2.6	-0.4	-2.4	34.3	31.1	18.0	5.5	4.9	4.3	73.1	63.1	39.3	22.5	27.8
BARC	5.4	1.6	0.5	-1.6	-3.8	-4.1	0.8	39.0	31.7	4.6	4.4	0.7	5.3	114.3	107.8	108.8	149.7	169.0
LLOY	10.4	8.8	7.8	5.4	3.0	2.3	0.8	16.4	-12.0	-8.0	0.9	4.1	6.6	75.7	65.8	92.0	117.8	186.7
DGE	6.7	6.4	6.2	5.9	5.6	4.9	-1.1	19.5	10.8	4.5	1.8	0.1	5.8	49.1	23.3	9.5	3.8	-0.3
BG.	7.1	5.5	6.1	4.2	1.2	-0.5	0.4	33.5	27.2	10.0	4.3	1.9	6.2	103.7	72.3	89.5	102.5	145.6
REED	8.6	8.2	8.0	7.7	7.2	6.0	0.4	10.1	8.0	4.8	3.4	2.3	4.7	24.4	15.1	7.6	4.5	1.7
CGNU	8.3	6.0	4.3	1.8	0.3	-0.2	-1.8	-4.0	-8.1	-6.7	-0.2	-0.5	2.9	59.3	58.1	77.3	121.4	148.8
TSCO	7.8	5.7	4.0	1.6	-0.1	-0.2	0.4	1.8	-9.5	-6.5	0.5	3.5	6.4	57.0	61.8	74.7	143.5	163.2
XTA	5.8	5.6	5.1	3.2	0.7	-2.0	-2.7	17.9	6.0	2.1	0.7	0.2	3.5	59.8	45.5	60.7	61.1	160.0
BA.	5.9	4.3	3.3	1.9	0.8	0.1	0.3	10.0	1.6	3.3	2.3	3.3	3.7	21.0	17.3	15.9	15.7	16.2
BATS	6.0	4.2	3.0	0.8	-1.4	-1.4	0.6	18.9	-7.2	-3.8	2.0	1.4	5.1	73.6	57.1	83.9	122.2	158.3
RTR	9.7	7.6	5.0	2.7	0.8	0.8	1.2	5.1	-9.3	-2.5	-0.2	4.0	7.7	65.5	66.1	76.2	111.0	163.4
STAN	12.1	9.9	9.1	5.8	2.6	1.5	-0.4	9.4	-9.9	-3.8	-0.6	0.8	6.7	66.0	54.6	71.3	114.0	135.0
HBOS	6.7	4.9	3.3	1.3	-0.3	-1.4	1.4	12.0	-9.3	-5.3	0.4	3.4	6.3	66.0	56.7	72.7	133.0	160.3
IMT	10.5	7.7	5.0	2.6	0.5	-0.8	-0.8	3.2	-9.5	-2.9	-0.3	2.0	7.4	69.8	58.8	71.2	109.1	138.0
BAY	9.8	7.4	6.2	3.1	0.5	-0.4	-0.2	15.1	-3.3	-0.5	2.0	3.0	6.9	61.4	58.2	78.5	112.4	159.9
AZVZ	8.6	5.9	4.4	2.3	0.8	1.1	-0.6	-3.8	-8.6	-5.7	-1.1	2.4	2.7	53.7	55.2	68.4	105.8	130.7
ICI	10.1	7.6	5.4	2.5	0.6	0.5	-0.3	11.4	-6.6	-2.8	-2.4	1.7	4.7	59.8	54.0	69.6	126.8	121.9
CCL	5.6	4.5	4.3	2.0	0.1	NAN	-2.7	12.0	0.8	0.0	-0.9	NAN	3.6	74.7	56.5	75.9	95.6	NAN
CBRY	8.2	5.5	3.7	1.5	-0.7	-1.3	0.0	0.6	-8.0	-5.8	2.1	1.3	5.1	60.1	60.2	82.8	114.3	122.2
NXT	10.1	7.8	7.5	4.1	1.6	-0.1	0.9	12.6	2.7	-1.1	2.9	3.1	6.8	54.5	49.6	59.5	74.5	133.2
LAND	9.2	6.6	4.1	1.5	-0.4	-1.1	-1.9	-2.2	-9.3	-4.6	-2.0	1.7	5.4	53.5	47.8	61.4	88.9	130.1
GLH	10.8	8.2	6.4	3.5	1.1	-0.2	-0.1	8.7	-6.7	-1.2	1.4	2.5	6.2	53.2	45.8	61.9	91.6	127.5
SMIN	10.0	7.5	6.1	4.2	2.8	2.4	-0.9	-1.8	-9.2	-4.5	0.2	2.5	3.4	52.4	50.6	69.3	98.4	112.3
BSY	8.7	6.5	4.2	2.2	0.0	-0.4	-1.4	5.7	-10.9	-5.3	0.3	1.2	5.5	56.7	49.6	65.2	92.9	125.1
RR.	6.2	3.7	1.9	-0.1	-1.4	-1.5	0.1	-0.8	-6.4	-5.0	0.1	0.6	8.3	55.0	56.3	86.2	117.8	140.6
PRU	5.1	3.6	2.3	0.6	-0.5	-1.1	-1.5	18.1	-3.8	-1.2	2.0	2.8	3.1	61.9	52.6	74.5	141.4	140.6
SSE	9.4	9.0	8.9	8.5	8.2	7.8	-2.9	9.1	4.5	1.0	-1.9	-1.6	2.9	27.1	12.4	4.4	-0.2	-1.1
LOG	7.9	7.6	7.5	7.1	6.6	5.8	1.4	13.2	8.1	5.2	3.4	2.2	4.6	29.0	16.1	7.9	4.1	2.6
UU.	7.9	7.6	7.4	7.1	6.6	5.9	0.9	10.8	7.3	5.3	3.2	1.3	5.8	23.5	14.7	9.2	5.2	1.7
NRK	13.2	9.7	7.5	4.0	1.9	1.5	1.3	13.6	-4.4	-2.4	-0.9	2.6	7.6	55.5	43.9	56.8	95.8	128.4
BT.A	6.2	4.6	3.8	1.9	-0.1	-0.6	-1.7	9.3	-9.0	-8.1	-0.4	0.6	2.2	54.2	50.1	56.3	104.6	157.1
KEL	7.1	3.9	2.1	-0.5	-2.5	-2.8	-1.6	-4.1	-10.9	-6.9	-2.0	2.6	5.2	41.4	43.2	60.1	83.2	116.7
NPR	7.8	7.4	7.2	6.9	6.7	6.1	-2.5	6.6	3.7	0.9	-0.3	-0.7	6.6	23.1	13.2	6.4	2.6	0.3
SBRY	10.9	10.4	10.2	9.8	9.4	8.4	-3.4	7.9	3.9	0.4	-0.9	-2.4	1.8	23.4	13.2	5.7	2.7	1.0
CPI	12.0	9.1	6.4	3.8	1.9	1.5	0.7	2.2	-4.0	-1.1	0.5	3.8	7.3	51.1	47.3	64.3	93.7	129.4
LMI	9.5	7.2	6.8	3.7	1.1	-0.8	-2.8	9.7	1.0	1.1	0.0	0.6	3.4	62.4	53.9	71.5	95.3	146.0
BDEV	13.9	13.0	10.7	8.0	3.0	1.0	-1.3	12.0	6.5	2.0	2.8	2.3	7.0	48.6	43.0	52.3	65.1	94.6
LGEN	8.8	8.3	7.9	7.4	4.2	0.4	-2.2	20.5	13.9	7.9	5.3	0.8	2.1	50.5	39.7	28.3	40.4	76.5
WMPY	10.8	6.7	4.7	1.4	-0.2	-0.6	-0.1	-0.7	-6.4	-2.4	0.9	2.4	7.8	41.4	46.6	51.2	88.8	126.1
ANTO	11.7	8.5	8.0	3.3	0.1	NAN	-0.9	9.9	-1.4	-1.4	1.9	NAN	8.3	60.9	41.1	55.7	80.4	NAN
TATE	11.0	8.2	5.9	3.7	1.3	1.1	-0.7	-0.9	-6.6	-2.0	1.0	1.8	5.5	51.6	46.7	63.5	106.4	115.3
YELL	9.7	9.0	7.6	5.6	1.5	-0.1	-2.2	12.6	6.6	4.3	3.4	1.9	4.2	52.6	43.0	56.6	63.0	103.8
III	11.2	8.7	6.9	4.5	1.5	0.2	-0.1	9.0	-9.0	-4.9	0.5	2.7	7.9	59.8	56.2	57.9	81.1	128.5
ETI	10.9	8.5	7.0	3.9	1.8	0.6	-0.8	6.5	-6.0	-2.2	-1.0	2.2	6.2	47.4	39.1	53.5	68.4	91.4
KGF	5.9	4.2	2.9	0.9	-0.6	NAN	-0.3	9.7	-4.4	-3.1	-2.0	NAN	3.4	49.1	38.5	45.0	59.9	NAN

Table 7a: Diebold and Mariano t-test for comparison between DEAR and ARFIMA on truncated out of sample forecast errors for various loss functions and horizons for 100 liquid LSE stocks. Positive values indicate outperformance of DEAR over ARFIMA. Values greater than 2 in absolute terms indicate a statistically significant difference.

Stock Name (Code)	**Loss Function: Error. Periods Ahead:**						**Loss Function: Absolute Error. Periods Ahead:**						**Loss Function: Square Error. Periods Ahead:**					
	1	**3**	**5**	**10**	**20**	**50**	**1**	**3**	**5**	**10**	**20**	**50**	**1**	**3**	**5**	**10**	**20**	**50**
SGE	11.1	9.5	8.6	6.7	5.3	4.1	-1.4	10.7	2.8	0.3	-0.1	1.8	4.5	10.1	9.5	7.2	6.9	6.9
SVT	6.7	5.4	5.1	3.5	1.5	-0.5	-1.0	23.9	14.7	9.3	3.8	0.3	3.0	40.8	36.6	29.6	36.4	53.3
IHG	7.2	4.8	4.6	1.2	-1.3	-2.4	-0.3	13.1	0.6	1.1	1.5	0.6	5.9	60.9	46.5	50.9	68.9	74.6
AUN	12.7	12.2	12.0	11.8	11.5	11.3	-0.2	3.8	2.2	1.3	0.2	0.9	5.5	11.3	6.8	4.1	1.6	1.4
DXNS	11.8	8.9	6.9	5.4	3.0	2.6	-0.8	-0.2	-5.1	-4.2	1.8	0.9	5.0	45.8	52.5	59.4	78.1	115.7
CW.	1.6	0.3	-0.9	-2.0	-3.2	-2.9	-2.2	-0.9	1.9	10.9	8.5	2.9	-2.2	39.1	46.9	70.5	96.9	77.4
CAN	9.1	5.9	4.7	2.6	0.7	0.2	0.6	-1.9	-10.3	-6.6	0.1	1.6	5.3	49.6	55.7	67.1	86.4	100.1
BB.	11.5	11.2	11.0	10.7	10.2	9.2	-0.5	6.4	4.2	3.0	2.2	0.5	4.3	14.6	8.6	5.7	3.6	0.4
PSN	14.1	10.9	10.3	5.9	2.4	0.5	0.7	10.2	-0.5	0.5	0.0	0.6	9.7	57.6	43.4	48.8	63.0	104.6
TWOD	10.6	7.8	7.5	4.2	1.5	0.4	-0.1	12.3	2.4	0.7	0.9	1.5	5.5	57.4	38.6	53.3	64.1	89.7
LII	10.6	6.0	4.3	1.9	0.0	-0.6	-1.4	-3.3	-7.5	-3.8	-1.0	1.1	3.4	33.6	34.7	39.1	47.7	60.5
ABF	9.0	8.8	8.6	8.2	7.8	7.5	-0.9	5.9	4.0	2.7	0.6	0.2	5.6	16.0	10.3	6.9	2.7	0.8
HMSO	10.0	7.4	6.8	2.9	0.1	-0.7	-0.2	10.6	-1.4	-2.8	0.8	1.3	6.4	47.4	34.3	51.9	63.3	92.1
WPP	8.2	8.0	7.8	7.5	7.2	6.8	-0.4	9.0	6.1	3.5	2.2	0.3	6.0	22.8	13.6	7.9	4.5	0.7
SPW	11.2	9.1	6.8	4.7	2.2	2.7	-0.3	6.5	-9.2	-2.3	0.2	0.3	5.4	55.7	52.9	62.1	88.3	130.3
RSA	6.4	6.1	5.9	5.6	5.2	4.3	-2.7	10.9	6.7	2.2	0.4	-2.3	2.2	32.0	20.2	9.1	4.1	1.6
CNE	9.2	6.5	6.0	2.4	0.3	-1.2	-1.3	10.8	-2.4	-0.4	-0.5	2.1	4.4	48.1	38.4	50.3	71.0	101.9
MRW	7.5	5.0	2.4	0.4	-2.0	-2.3	-2.6	3.4	-7.5	-3.8	0.1	0.6	3.9	42.7	40.8	54.3	60.9	78.9
WMH	12.5	9.8	7.1	4.3	2.2	2.0	0.8	3.9	-5.0	-4.3	-0.3	2.1	6.2	46.0	39.0	51.5	65.0	118.6
GUS	5.6	5.4	5.3	5.1	4.8	4.2	-0.4	10.4	6.6	2.3	1.5	0.8	4.0	24.5	15.5	4.8	2.2	0.0
EMI	12.0	8.4	7.5	3.0	0.4	-0.8	-2.7	8.4	-1.9	-2.6	0.3	1.1	5.6	41.8	37.1	59.5	78.8	112.3
JMAT	9.5	9.1	8.9	8.5	8.3	8.2	-1.3	3.8	3.8	2.7	0.1	1.2	7.4	13.3	11.9	8.8	3.7	3.5
EMA	11.3	8.2	5.3	2.2	0.4	0.9	1.0	3.5	-2.8	-2.6	2.6	1.6	8.0	55.8	58.7	71.4	91.0	107.1
EZJ	9.6	9.2	8.9	6.8	2.8	0.0	-0.5	8.4	5.1	2.6	3.8	3.0	6.9	33.5	28.4	26.9	54.5	85.5
VED	6.9	6.7	6.6	5.8	3.1	0.7	-2.1	8.8	3.8	0.3	2.9	1.6	5.0	37.5	26.1	32.0	66.5	100.4
FP.	10.0	9.6	9.5	9.2	8.8	8.2	-1.4	6.9	3.9	1.4	0.3	-1.2	4.7	26.2	12.8	5.1	2.4	-0.6
BOC	5.2	4.9	4.7	4.5	4.1	3.5	0.9	11.4	8.1	5.2	1.6	1.1	3.0	19.2	12.3	6.5	1.7	1.1
ARI	12.9	8.6	6.7	3.9	2.3	2.2	-0.1	-0.9	-4.0	-4.9	-0.1	3.2	5.4	41.1	41.0	49.1	67.1	122.1
PFG	13.7	13.2	12.5	9.2	4.7	1.1	0.7	10.5	5.7	3.8	2.8	0.4	6.7	23.0	18.8	19.9	19.8	20.5
ITV	7.6	7.3	7.2	6.9	6.1	3.6	-0.5	16.3	11.2	5.5	2.1	-0.5	4.8	42.9	26.1	13.6	8.4	7.8
HG	6.0	5.7	5.6	5.3	4.9	4.0	-0.4	10.7	7.5	4.7	2.3	0.5	5.3	27.1	16.4	9.8	5.2	1.0
SLOU	9.7	7.4	5.5	3.0	1.3	1.1	-1.1	0.2	-8.6	-4.8	-1.9	0.5	3.7	41.0	39.1	44.0	72.5	93.0
MSY	10.5	9.9	8.3	5.6	2.1	0.2	0.4	10.5	7.2	3.1	1.6	2.0	5.4	31.5	32.8	40.5	45.9	79.3
HAS	6.7	6.4	6.2	5.9	5.3	4.2	-0.2	8.6	6.0	3.2	-0.1	0.5	4.3	30.7	19.8	9.8	3.7	3.6
SHP	6.1	5.9	5.7	5.5	5.2	4.6	-2.0	5.6	2.4	0.2	-1.0	-1.4	2.2	15.5	9.4	3.2	0.2	-1.1
MAB	7.8	7.1	6.0	3.5	1.0	-0.2	-0.2	8.2	4.8	2.6	1.4	2.4	5.6	39.9	41.0	51.6	73.7	96.8
TNI	9.8	9.7	9.5	9.2	9.0	8.6	-1.1	5.1	3.5	2.4	0.5	0.9	6.8	16.1	11.1	7.7	3.5	2.8
PRTY	6.3	5.5	4.8	2.9	0.7	-0.5	0.3	8.8	4.6	3.9	3.3	2.6	4.6	31.2	31.6	39.2	56.6	66.9
UBM	8.7	8.4	8.1	7.7	7.3	6.7	1.1	8.7	6.3	4.6	3.0	1.8	7.4	18.7	12.6	8.9	6.1	3.2
KESA	10.3	10.0	9.9	9.7	9.3	NAN	0.1	4.3	3.7	2.4	1.9	NAN	7.0	13.1	11.5	8.4	6.1	NAN
RTO	5.2	4.9	4.7	4.4	4.0	3.4	-1.4	4.2	2.6	1.9	0.6	-0.1	2.3	12.3	6.3	3.5	0.4	-2.4
PILK	2.7	2.5	2.3	2.1	1.7	NAN	0.3	2.6	2.6	2.2	1.9	NAN	3.4	4.5	3.5	1.7	0.5	NAN
PNN	11.3	11.3	11.3	11.1	7.0	NAN	0.2	6.0	2.3	1.1	1.7	NAN	7.9	24.9	19.7	17.7	33.4	NAN
RB.	3.2	-14.8	-19.4	-27.3	-61.7	-105.9	-3.4	0.0	5.0	16.7	58.9	87.9	-1.3	33.0	40.0	43.0	86.4	162.3
SN.	3.8	-15.9	-19.7	-24.9	-72.5	-152.6	-3.9	-0.6	11.3	21.6	57.6	73.2	-2.9	23.9	37.5	46.1	86.8	106.1
OML	1.8	-14.4	-18.2	-24.0	-37.5	-92.4	-2.4	17.9	13.6	22.2	39.8	77.8	-3.9	41.4	39.2	45.8	60.7	117.6
CPG	2.1	-13.7	-19.7	-27.4	-40.8	-169.1	-2.4	5.2	8.8	21.6	39.6	61.3	-0.9	28.3	26.4	33.7	50.4	84.0
mean	8.4	6.2	5.0	3.0	0.2	-4.1	-0.7	8.8	0.6	0.7	3.0	4.6	4.9	46.3	39.6	46.4	65.6	89.7
std	2.8	4.9	5.6	6.6	11.8	27.7	1.3	8.5	9.2	6.1	9.8	15.1	2.3	22.1	20.9	30.2	49.3	66.5
min	1.6	-15.9	-19.7	-27.4	-72.5	-169.1	-4.3	-7.5	-21.3	-11.5	-2.4	-3.7	-3.9	4.5	3.5	1.7	-0.2	-3.3
max	14.1	13.2	12.5	11.8	11.5	11.3	1.4	39.0	31.7	22.2	58.9	87.9	9.7	114.3	107.8	120.9	200.1	273.5

Table 7b: Continuation of previous subtable.

Stock Name (Code)	**ARFIMA Forecasts (Horizons)**						**DEAR Forecasts (Horizons)**					
	1	**3**	**5**	**10**	**20**	**50**	**1**	**3**	**5**	**10**	**20**	**50**
RDSB	78.02	63.59	60.01	53.87	51.02	49.92	78.07	66.67	63.43	58.71	55.42	53.54
AZN	75.78	61.45	58.07	52.87	50.30	49.90	75.81	63.77	61.58	57.43	54.69	51.58
RDSA	77.15	62.12	58.24	52.89	50.40	49.99	77.23	65.25	60.46	55.32	53.01	50.95
BPA	82.42	68.67	62.40	57.22	54.87	54.38	82.43	70.65	67.69	62.12	57.45	51.48
BLT	74.28	60.24	57.25	52.56	50.73	50.01	74.31	63.66	61.06	57.42	54.99	52.01
RBOS	77.79	63.52	59.80	53.57	50.74	49.89	77.81	65.98	63.51	59.05	55.65	52.04
GSK	79.72	65.98	62.24	55.12	50.71	49.89	79.73	68.40	65.91	61.34	56.61	54.18
VOD	82.94	71.74	66.79	60.75	55.44	52.53	82.97	75.37	73.00	68.70	61.29	57.50
BARC	78.48	62.78	56.44	53.96	50.59	50.14	78.50	66.77	64.36	59.64	56.57	52.08
LLOY	79.88	65.88	62.06	54.97	51.20	49.97	79.92	68.43	65.54	60.66	56.90	53.79
DGE	77.63	62.98	58.23	55.37	54.31	53.27	77.66	65.91	63.22	59.10	55.80	52.73
BG.	77.58	63.39	55.67	53.36	50.72	50.05	77.64	67.47	64.11	59.60	55.41	52.92
REED	80.17	66.34	60.91	56.54	54.46	52.50	80.25	68.93	65.44	60.76	57.25	54.78
CGNU	78.42	64.71	61.15	54.92	50.72	50.25	78.45	66.90	64.68	60.80	54.23	52.46
TSCO	79.39	66.30	62.65	55.84	51.53	50.04	79.44	69.51	66.49	62.09	58.53	53.12
XTA	73.88	59.26	55.81	52.53	50.70	50.05	73.93	62.82	60.11	56.14	50.85	50.31
BA.	77.16	63.47	59.41	53.85	51.62	50.55	77.18	66.44	63.47	58.94	53.35	51.73
BATS	79.10	65.16	61.41	54.44	50.75	50.14	79.12	67.41	64.34	59.47	56.43	52.73
RTR	77.78	64.06	60.33	53.90	50.99	49.79	77.84	67.10	64.09	57.94	54.95	52.99
STAN	79.06	64.84	60.62	53.54	50.71	50.17	79.13	67.52	63.97	57.68	53.55	52.71
HBOS	79.06	65.51	61.27	54.59	50.82	50.03	79.08	68.50	65.37	59.08	54.57	54.20
IMT	78.28	63.88	59.57	53.35	50.71	50.03	78.34	66.32	62.81	57.43	52.46	51.46
BAY	76.53	62.45	58.81	53.37	50.73	49.84	76.61	65.45	62.50	58.81	55.64	51.54
AZVZ	77.22	63.03	58.74	53.39	50.69	49.81	77.26	65.51	60.78	54.27	51.68	51.14
ICI	76.46	62.00	58.80	53.53	51.14	50.08	76.51	64.82	62.51	57.40	53.28	52.48
CCL	75.52	61.24	57.41	52.75	51.15	NAN	75.59	64.54	61.30	57.22	54.24	NAN
CBRY	79.46	65.57	61.43	54.93	50.90	50.22	79.50	68.56	65.14	59.89	56.21	52.48
NXT	79.76	65.38	60.47	54.44	51.07	50.25	79.87	68.61	64.95	59.66	56.24	53.87
LAND	78.91	64.34	59.83	53.68	51.13	50.04	78.98	66.63	63.15	57.59	53.85	52.97
GLH	78.77	64.71	60.91	54.25	51.15	50.34	78.84	67.77	64.42	59.91	55.87	54.99
SMIN	77.73	63.26	59.93	53.89	50.71	49.85	77.79	65.94	62.83	57.40	52.81	51.74
BSY	78.88	65.15	60.92	54.39	51.18	50.09	78.94	68.22	64.33	58.38	56.45	51.70
RR.	76.05	62.48	58.73	53.35	50.73	50.21	76.15	65.30	62.64	56.62	53.26	51.39
PRU	77.31	63.59	60.25	53.66	50.82	49.91	77.34	66.35	64.06	59.26	55.98	52.84
SSE	79.00	64.64	59.39	55.46	53.64	52.87	79.07	68.09	65.06	58.29	52.42	51.86
LOG	77.02	62.36	57.21	53.08	51.29	49.60	77.08	66.28	62.56	57.57	54.73	52.05
UU.	77.32	62.44	58.13	55.03	52.78	50.93	77.36	66.10	63.18	59.25	55.57	52.78
NRK	77.92	63.54	60.00	53.78	51.03	49.93	78.01	66.29	64.11	59.50	52.82	52.21
BT.A	80.56	67.58	63.81	56.78	51.03	50.11	80.60	70.08	67.38	61.36	51.52	50.69
KEL	78.59	65.15	61.19	54.10	50.80	49.62	78.67	67.78	63.96	56.50	51.29	50.66
NPR	78.45	64.92	60.02	56.03	53.97	52.72	78.51	67.77	64.44	58.88	54.77	52.71
SBRY	78.32	63.82	59.39	55.68	54.28	53.04	78.38	67.08	64.32	59.36	55.39	51.59
CPI	77.70	63.21	58.94	52.97	50.79	49.66	77.77	65.89	61.92	56.88	54.04	52.62
LMI	75.46	60.89	57.22	52.47	50.61	50.24	75.50	64.72	60.83	56.90	51.62	51.24
BDEV	77.21	61.56	56.41	52.61	50.08	50.06	77.31	65.99	62.13	57.67	53.31	52.80
LGEN	79.47	66.50	62.12	55.35	52.21	50.46	79.52	69.66	67.88	62.81	58.21	50.21
WMPY	77.48	63.04	58.70	53.01	50.74	50.10	77.63	66.47	62.28	54.10	53.39	53.05
ANTO	76.83	61.58	57.41	52.04	49.99	NAN	76.90	65.41	62.05	53.81	52.76	NAN
TATE	78.26	64.19	60.09	53.91	50.85	49.95	78.34	66.90	63.33	58.57	54.14	50.80
YELL	77.67	63.49	58.51	53.10	50.16	50.21	77.78	67.76	64.41	58.17	53.20	52.06
III	80.08	66.14	61.56	54.60	50.56	50.02	80.12	68.79	64.59	59.05	53.63	52.74
ETI	80.12	65.40	61.03	54.38	51.33	49.98	80.20	68.92	64.42	58.43	53.83	52.68
KGF	79.60	66.18	62.27	55.63	52.07	NAN	79.67	69.28	65.12	59.36	53.59	NAN
SGE	78.61	64.35	59.42	55.04	52.66	51.14	78.67	66.96	63.74	58.78	55.19	53.33
SVT	79.83	66.08	61.26	54.29	51.32	50.07	79.85	68.74	65.64	60.42	54.68	50.60
IHG	77.18	62.84	58.93	53.35	51.24	50.58	77.25	66.16	62.82	58.06	54.85	52.75
AUN	75.04	60.28	56.80	54.38	53.06	52.35	75.26	64.30	60.93	57.55	53.97	53.72
DXNS	79.24	66.08	62.42	55.76	51.26	50.18	79.30	69.00	66.02	60.20	56.82	51.18
CW.	80.27	69.11	63.57	52.91	49.85	49.59	80.28	71.19	68.35	62.86	57.65	51.77

Table 8a: Percentage of correct out of sample forecasts.

Stock Name (Code)	ARFIMA Forecasts (Horizons) 1	3	5	10	20	50	DEAR Forecasts (Horizons) 1	3	5	10	20	50
CAN	78.63	65.08	61.58	55.36	51.27	50.28	78.70	68.18	65.43	60.47	57.41	53.90
BB.	74.96	60.59	56.08	53.38	52.12	51.26	75.01	64.08	60.19	56.66	54.65	51.57
PSN	79.98	65.35	60.65	54.11	51.48	50.52	80.10	68.64	64.55	59.01	54.87	53.62
TWOD	76.22	61.12	57.17	52.65	50.67	50.08	76.29	65.28	61.34	55.93	52.66	52.43
LII	78.14	64.07	58.91	53.58	51.25	50.39	78.21	65.73	61.08	55.50	53.61	53.29
ABF	78.56	64.84	59.85	55.77	53.31	51.68	78.64	68.04	64.52	59.51	53.77	52.34
HMSO	78.20	63.56	59.73	54.06	51.05	50.02	78.29	66.59	62.65	56.55	53.49	52.27
WPP	76.47	63.07	58.40	54.15	52.27	51.69	76.52	66.04	62.85	58.31	55.22	52.28
SPW	76.73	62.73	59.04	53.35	50.59	50.08	76.78	65.84	61.87	57.06	53.59	50.86
RSA	78.45	64.91	60.32	56.26	53.97	52.32	78.49	68.78	66.14	60.70	56.68	50.85
CNE	78.34	63.09	59.49	53.57	51.43	50.31	78.41	65.69	62.02	56.41	54.84	54.68
MRW	79.92	66.97	63.20	56.59	52.07	50.39	79.97	70.13	66.35	61.39	58.29	52.47
WMH	78.20	64.20	60.14	54.62	51.37	50.35	78.30	67.18	64.19	57.34	54.25	53.90
GUS	76.62	61.67	57.57	55.38	53.51	52.30	76.67	64.95	62.96	58.69	55.87	52.61
EMI	75.31	61.86	58.74	53.96	51.02	50.22	75.39	65.40	62.21	56.53	53.05	52.73
JMAT	77.91	64.46	58.85	54.01	51.80	50.45	77.97	65.96	63.23	59.00	52.80	52.02
EMA	76.70	62.71	58.54	53.52	50.19	50.23	76.76	65.90	62.76	57.80	54.85	53.86
EZJ	76.63	59.61	56.32	53.24	51.00	50.09	76.81	64.39	61.54	57.18	55.33	53.28
VED	72.99	58.15	56.00	53.32	51.73	50.54	73.09	62.96	60.85	56.88	55.56	54.02
FP.	80.11	66.32	61.13	56.58	53.81	52.76	80.19	70.02	66.93	59.95	56.83	53.12
BOC	78.47	64.83	60.02	56.32	53.52	52.63	78.56	68.72	64.72	60.13	54.66	52.78
ARI	75.80	62.68	58.52	53.88	50.81	50.08	75.92	64.60	60.76	55.57	54.08	54.06
PFG	76.57	59.82	56.13	52.38	50.70	50.57	76.80	65.52	61.28	57.47	53.72	52.39
ITV	78.31	65.98	61.10	55.68	53.48	51.62	78.38	69.75	66.89	62.89	59.04	52.01
HG	78.72	64.36	59.18	55.03	52.77	51.32	78.76	67.65	63.79	58.37	54.62	52.35
SLOU	77.75	64.26	59.82	54.18	51.07	50.21	77.86	65.88	61.39	54.65	52.12	51.60
MSY	75.95	59.99	55.53	52.18	50.58	49.89	76.13	64.90	61.25	58.02	54.44	53.71
HAS	77.66	64.44	60.44	56.01	53.80	52.69	77.73	68.39	65.66	60.70	56.07	53.48
SHP	76.54	61.09	57.28	54.44	53.39	52.21	76.58	63.83	61.69	56.29	53.53	50.86
MAB	73.63	58.97	56.05	52.39	50.69	50.01	73.81	63.26	60.21	55.63	53.11	52.34
TNI	75.52	60.95	56.39	52.74	51.02	50.29	75.59	65.44	61.61	56.17	52.31	51.61
PRTY	78.10	63.17	59.75	54.40	52.50	50.80	78.28	68.33	65.39	61.61	58.42	55.36
UBM	75.68	60.14	55.32	51.64	49.96	49.42	75.84	65.36	61.80	56.55	52.70	52.13
KESA	74.39	60.86	57.61	55.22	53.85	NAN	74.65	64.66	62.42	59.78	57.63	NAN
RTO	78.21	65.32	61.46	57.28	54.69	53.73	78.31	68.17	63.92	59.84	55.65	52.76
PILK	73.34	66.45	64.09	61.88	61.69	NAN	74.13	67.41	66.04	63.23	61.45	NAN
PNN	74.73	56.41	53.27	51.34	49.95	NAN	75.04	62.74	59.23	55.24	53.22	NAN
RB.	92.20	85.39	83.05	75.34	56.77	52.93	92.20	87.93	87.91	87.93	87.99	88.12
SN.	92.60	86.67	81.45	73.43	53.68	49.16	92.60	88.59	88.58	88.59	88.53	88.74
OML	91.93	82.01	81.74	77.00	63.91	49.46	91.93	87.92	87.91	87.88	87.96	88.06
CPG	91.80	85.16	83.06	75.93	58.33	47.53	91.81	87.91	87.92	87.82	87.76	87.72
mean	78.31	64.48	60.35	55.18	51.96	50.62	78.39	67.70	64.59	59.75	56.15	54.05
std	3.37	4.81	5.02	4.46	2.20	1.15	3.33	4.65	5.28	6.23	6.84	7.33
min	72.99	56.41	53.27	51.34	49.85	47.53	73.09	62.74	59.23	53.81	50.85	50.21
max	92.60	86.67	83.06	77.00	63.91	54.38	92.60	88.59	88.58	88.59	88.53	88.74

Table 8b: Continuation of previous subtable.

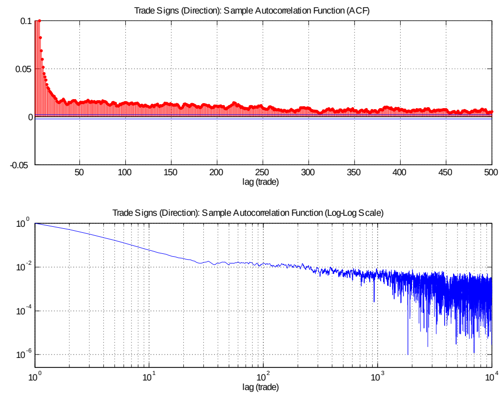

Figure 1: AZN - Sample autocorrelation function of trade direction (sign). The top subplot is the usual autocorrelation function with 95% confidence intervals for statistical significance while the bottom one uses double logarithmic scale so that a linear decline suggesting long memory.

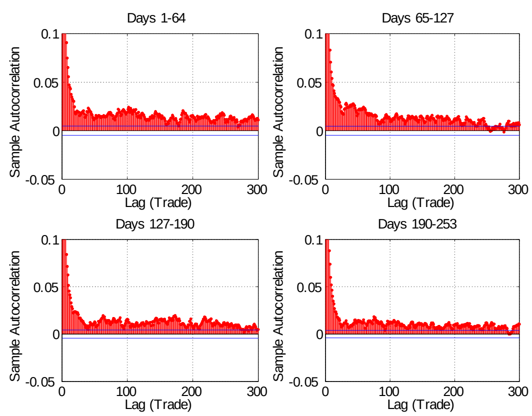

Figure 2: AZN - Autocorrelation function of the trade direction time series for four subsets which span the original sample presented in figure 1.

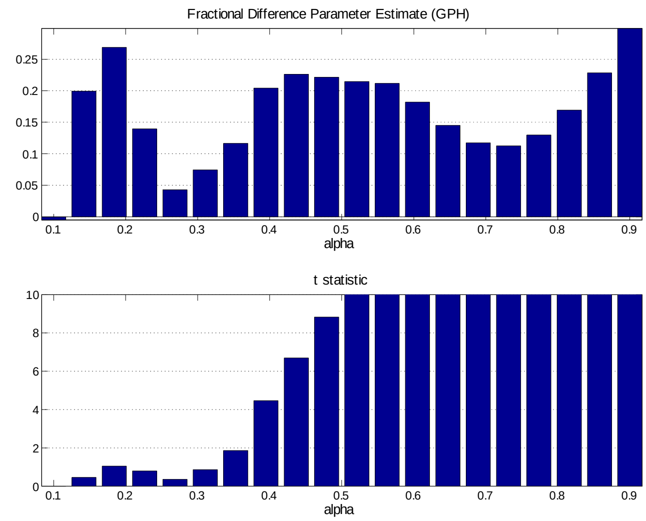

Figure 3: AZN - Upper subplot: GPH estimates of the fractional difference parameter for various choices of alpha. The relation $N = T^{alpha}$ determines the number of lower frequencies used in the GPH regression for a given series length T. Bottom subplot: Corresponding t statistics, truncated at 10.

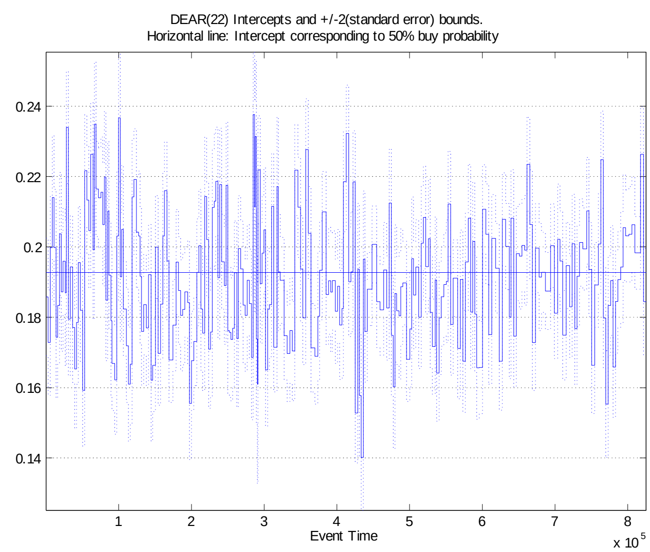

Figure 4: AZN - DEAR(22) daily effect intercept estimates and their confidence intervals in trade time. The horizontal line represents the value of the intercept that corresponds to 0.5 buy probability for the estimated values of other AR parameters.

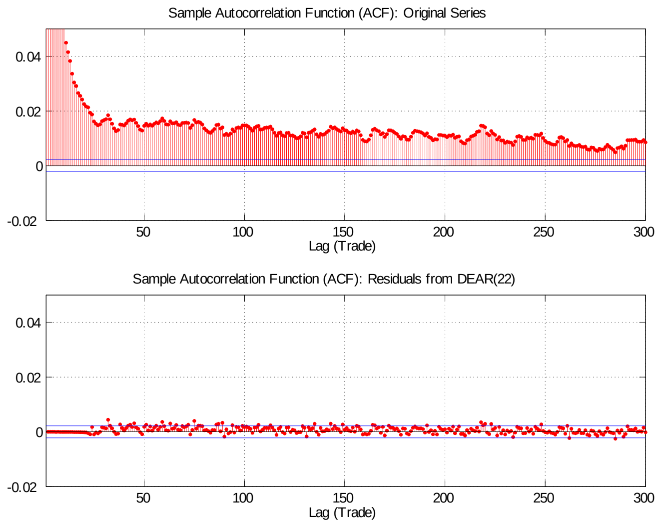

Figure 5: AZN - Sample autocorrelation function of the trade direction (sign) time series (upper subplot) and DEAR(22) residuals (bottom subplot).

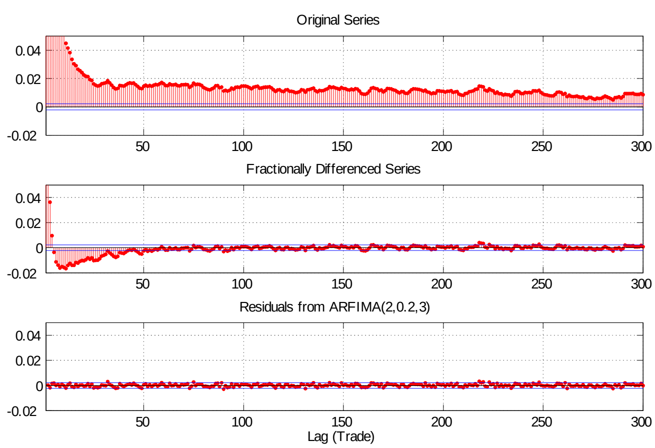

Figure 6: AZN - Sample autocorrelation function of the trade direction (sign) time series (upper subplot) and residuals after fractional differencing (middle subplot) and full ARFIMA estimation (bottom subplot).

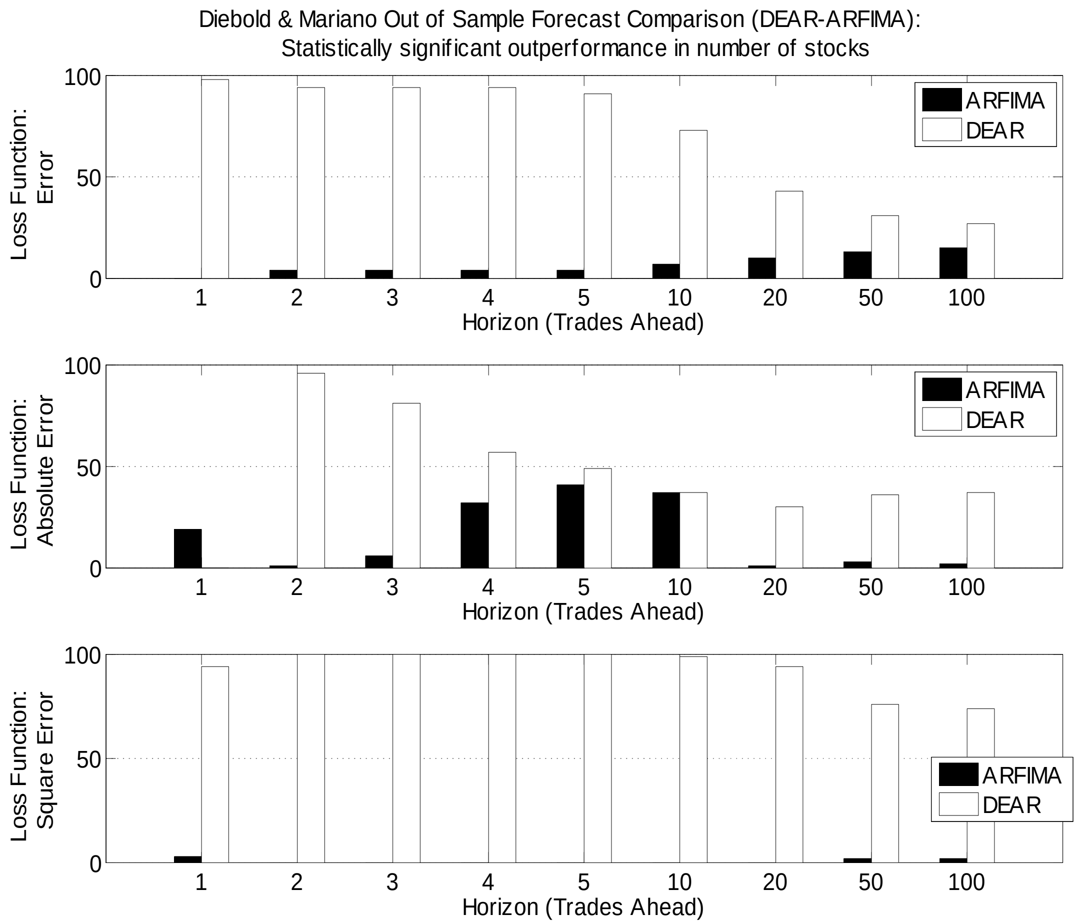

Figure 7: Subplots display the number of LSE stocks (total 100) for which DEAR outperforms ARFIMA or (vice versa) in terms of the Diebold and Mariano test at the 5% level for various loss functions and horizons.

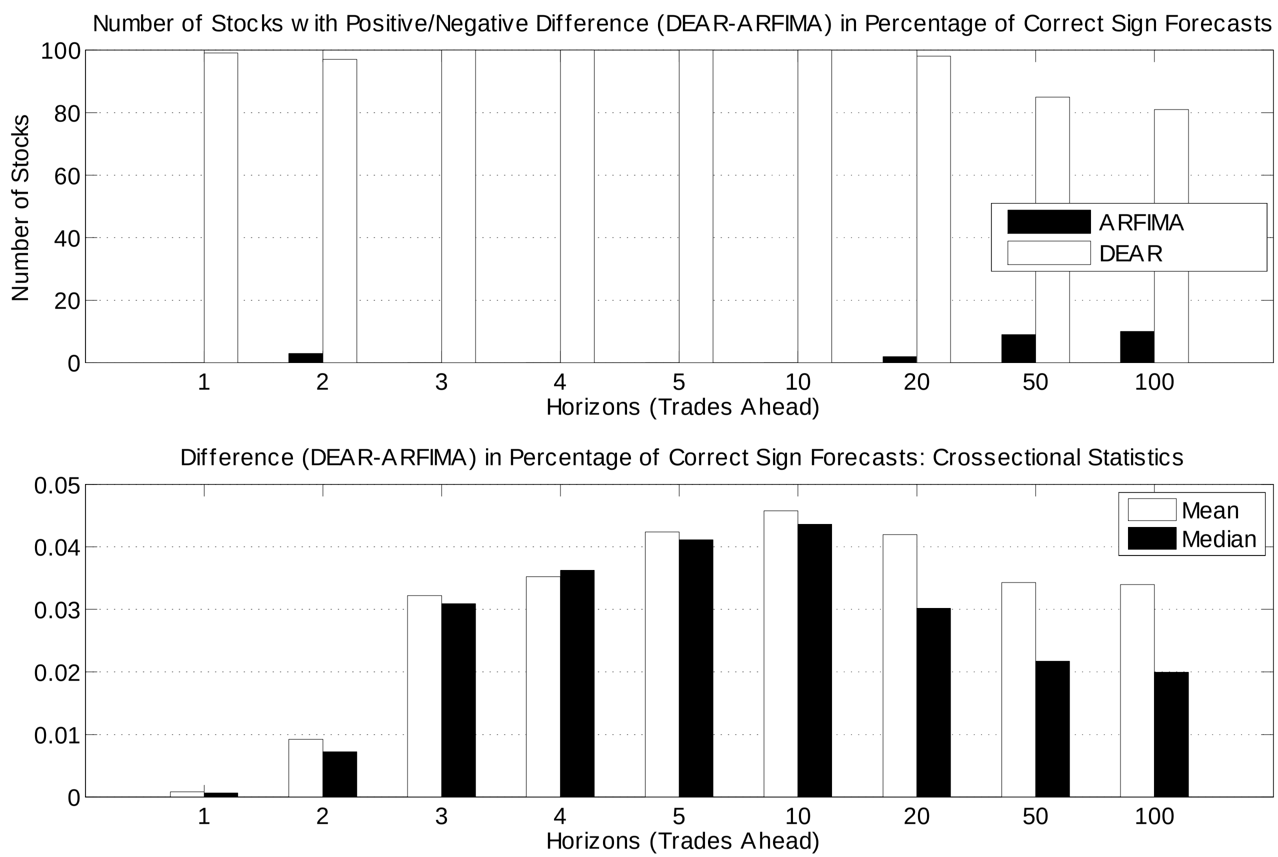

Figure 8: Upper subplot shows the number of stocks (total 100) for which the difference in the percentage of correct sign forecasts is positive, in favor of DEAR or negative in favor of ARFIMA. Bottom subplot measures the mean and median of this difference across stocks.