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AND FRACTIONAL INTEGRATION ANALYSIS

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Abstract

This paper provides some new empirical evidence on the weekend effect, one of the most recognized anomalies in financial markets. Two different methods are used: (i) a trading robot approach to examine whether or not there is such an anomaly giving rise to exploitable profit opportunities by replicating the actions of traders; (ii) a fractional integration technique for the estimation of the (fractional) integration parameter d. The results suggest that trading strategies aimed at exploiting the weekend effect can generate extra profits but only in a minority of cases in the gold and stock markets, whist they appear to be profitable in most cases in the FOREX. Further, the lowest orders of integration are generally found on Mondays, which can be seen as additional evidence for a weekend effect.

Keywords: *Efficient Market Hypothesis; weekend effect; trading strategy.*

JEL classification: *G12, C63*

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1. Introduction

Detecting calendar effects (anomalies) in financial markets is of interest both to traders aiming to exploit them to gain extra profits and to researchers analysing whether there is evidence of market failure and of the inadequacy of the Efficient Market Hypothesis (EMH). Several papers have tested for their presence using a variety of empirical methods. One of the most frequently studied anomalies is the weekend effect (Monday effect, day of the week effect) first discussed by French (1980), namely the tendency of financial assets to generate negative returns on Mondays. Different theories have been developed to account for its presence. In behavioural finance models it is attributed to the negative expectations of investors considering Monday the worst day of the week. Another possible explanation is that over the weekend market participants have more time to analyse price movements and as a result on Mondays a larger number of trades takes place. Alternatively, it might be due to deferred payments during the weekend, which create an extra incentive for the purchase of securities on Fridays leading to higher prices on that day.

Overall, the empirical evidence is still mixed. The present study provides some new results based on two different methods: (i) a trading robot approach to examine whether or not there is such an anomaly giving rise to exploitable profit opportunities by replicating the actions of traders; (ii) a fractional integration technique for the estimation of the (fractional) integration parameter d.

The remainder of the paper is structured as follows: Section 2 briefly reviews the literature on the weekend effect. Section 3 outlines the empirical methodology. Section 4 presents the empirical results. Section 5 offers some concluding remarks.

2. Literature Review

Fields (1931) suggested that the best trading day of the week is Saturday. Another important study on the weekend effect is that by Cross (1973), who analysed the Friday-Monday data for the Standard & Poor's Composite Stock Index from January 1953 to December 1970 and found an increase on Fridays and a decrease on Mondays.French (1980) extended the analysis to 1977 and also reported negative returns on Mondays. Further contributions by Gibbons and Hess (1981), Keim and Stambaugh (1984), Rogalski (1984), and Smirlock and Starks (1986) also found the positive-Friday / negative-Monday pattern. Connolly (1999) also allowed for heteroscedasticity but still detected a Monday effect from the mid- 1970s.Rystrom and Benson (1989) explained the presence of the day-of-the-week effect on the basis of the psychology of investors who believe that Monday is a "difficult" day of the week and have a more positive perception of Friday. Ariel (1990) argued against a connection between the weekend and the Monday effect. Agrawal and Tandon (1994) examined 19 equity markets around the world, and found the day-of-the -week effect in most developed markets. Sias and Starks (1995) associate the weekend effect with stocks in large portfolios of institutional investors. Research conducted in Fortune (1998, 1999) shows that it has a tendency to disappear and is a phenomenon with two components: the first is the "weekend drift effect", i.e. stock prices tend to decline over weekends but rise during the trading week; the second is the "weekend volatility effect", i.e. the volatility of returns during weekends is less per day than that over contiguous trading days.

As for the role of short-selling, Kazemi, Zhai, He and Cai (2013) and Chen and Singal (2003) explain the weekend effect as resulting from the closing of speculative positions on Fridays and the establishing of new short positions on Mondays by traders. However, the results of the study by Christophe, Ferri and Angel (2007) do not support this conclusion. Further evidence is provided by Singal and Tayal (2014) for the futures market, Olson, Chou, Mossman (2011) who carry out various breakpoint and stability tests, and Racicot (2011) who uses spectral analysis. The findings from other relevant studies are summarised in Table 1.

Table 1 Weekend effect: an overview of recent researches

<table>
<tr><th>Author</th><th>Type of analysis</th><th>Object of analysis (time period, market, index)</th><th>Results</th></tr>
<tr><td>Sias, Starks (1995)</td><td>Hypothesis testing (t-test and F-test)</td><td>1977-1991 market equity capitalization, institutional holdings, daily returns and volume of 1500 institutional investors on the NYSE</td><td>The weekend effect is driven primarily by institutional investor trading patterns</td></tr>
<tr><td>Fortune (1998)</td><td rowspan="2">Jump diffusion model of stock returns</td><td>January 1980 -June 1998 - daily close-to-close data for the S&P 500</td><td>The negative weekend drift appears to have disappeared although weekends continue to have low volatility</td></tr>
<tr><td>Fortune (1999)</td><td>January 1980 - January 1999 daily close-to-close data of the Dow 30, the S&P 500, the Wilshire 5000, the Nasdaq Composite, and the Russell 2000</td><td>The weekend drift effect is a financial anomaly that will ultimately correct itself.</td></tr>
<tr><td>Schwert (2003)</td><td>Correlation analysis</td><td>1885–1927 - the Dow Jones indexes portfolio; 1928–2002 - the S&P composite portfolio</td><td>The weekend effect seems to have disappeared since the 1980-s</td></tr>
<tr><td>Chen, Singal (2003)</td><td>Descriptive and regression analysis</td><td>July 1962 - December 1999 - New York Stock (NYSE); December 1972 - December 1999 - Nasdaq - daily returns for stocks; June 1988 - December 1999 Nasdaq and January 1988 – 1999 NYSE - monthly short interest data</td><td>Speculative short sales can explain the weekend effect.</td></tr>
<tr><td>Hsaio, Solt (2004)</td><td>one-tailed nonparametric test based on the approximated normal distribution and parametric test to examine the</td><td>January 1988 to December 2000 (678 weeks) - the 3:00 and closing values for the S&P 500 index; April 1988 to December 2000 (669 weeks) - the CREF stock, growth, and</td><td>Presence of weekend effect in the average daily returns for many of the tested portfolios till 2000.</td></tr>
</table>

	strategies' market timing ability	money market account; April 1994 to December 2000 (332 weeks) – growth account	
Christophe, Ferri, Angel (2007)	Descriptive and regression analysis	September 2000 - July 2001 daily 9:30 am-4:00 pm data on NASDAQ-listed stock	Speculative short-selling does not explain the Monday-Friday difference in returns
Olson, Chou, Mossman, (2011)	Regression analysis, Chow breakpoint tests, Bai-Perron Tests	1973 – 2007 - the Dow-Jones 30 Industrials, Standard and Poor's 500, Standard & Poor's Midcap 400, Standard & Poor's Smallcap 600, NASDAQ 100, American Stock Exchange (AMEX) Composite indices	The weekend effect may have already gone through its entire involving identification, exploitation, decline, reversal, and disappearance. There is no significant weekend effect in U.S. small stocks after about mid 2003
Racicot (2011)	Spectral analysis	1970-1973 - S&P500 index	Spectral analysis confirms the Monday effect.
Kazemi, Zhai, He and Cai (2013)	Descriptive and regression analysis	January 1980 – present time, 60 market indices from 59 countries (For all countries, except US, major stock index is used. For the US both the Dow Jones Index and the S&P 500 were used)	During the period from 1980 to 1994, short sales can explain the weekend effect. During the period from 1995 to 2007, the cross-sectional weekend effect cannot be explained by short sales.
Singal and Tayal (2014)	Descriptive and regression analysis	1990 – 2012, eight futures: Crude oil, Heating Oil, Soybeans, Sugar, S&P 500 Index, British Pound, 10-Year Treasury Note, and Gold	Evidence of the weekend effect in futures markets shows that security prices will generally be biased upwards, with greater overvaluation for more volatile securities. Unconstrained short selling is not a sufficient condition for unbiased prices

3. Data and Methodology

We use daily data for 35 US companies included in the Dow Jones index and 8 Blue-chip Russian companies. The sample period for the US and Russian stock markets covers the period from January 2005 and 2008 respectively till the end of April 2014. We also analyse the FOREX using data on the six most liquid currency pairs (EURUSD, GBPUSD, USDJPY, USDCHF, AUDUSD, USDCAD) and gold prices over the period from January 2000 and 2005 respectively till the end of April 2014.

Our first (trading-bot) approach considers the weekend effect from the trader's viewpoint, namely whether it is possible to make abnormal profits by exploiting it. Specifically, we programme a trading robot which simulates the actions of a trader according to an algorithm (trading strategy). To test it with historical data we use a MetaTrader trading platform which provides tools for replicating price dynamics and trades according to the adopted strategy.

We examine two trading strategies:

- **Strategy 1:** Sell on Friday close. Close position on Monday close.
- **Strategy 2:** Sell on Monday open. Close position on Monday close.

If a strategy results in the number of profitable trades > 50% and/or total profits from trading are > 0, then we conclude that there is a market anomaly.

Our second approach is based on estimating the degree of integration of the series for different days of the week. Specifically, we use the Whittle function in the frequency domain, as in following model:

$$y_t = \alpha + \beta t + x_t ; \quad (1-L)^d x_t = u_t , \qquad (*)$$

where y_t is the observed time series; α and β are the intercept and the coefficient on the linear trend respectively, x_t is assumed to be an I(d) process where d can be any real number, and u_t is assumed to be weakly autocorrelated. However, instead of specifying a parametric ARMA model, we follow the non-parametric approach of Bloomfield (1973), which also produces autocorrelations decaying exponentially as in the AR case. If the estimated order of integration for a particular day, specifically Monday, is significantly different from that for the other days of the week, then it can be argued that there is evidence of a weekend effect.

4. Empirical Results

Detailed results are presented in the Appendix. Table 1 summarises those for Strategy 1.

Table 1a: Summary of testing results for Strategy 1

Type of a market	Totaltrades	Profittrades	Profittrades % oftotal	Totalnetprofit	Profittrades %>50, %	Profit>0, %
US stock market	434	201	46%	-1334	14%	26%
Russian stock market	325	141	43%	-285	0%	13%
FOREX	724	357	49%	7726	50%	50%
GOLD	453	210	46%	-18733	0%	0%

In general this strategy is unprofitable in the stock markets (both US and Russian) and in gold market but can generate profits in the FOREX. However, in the latter case, the number of profitable trades is less than 50%, and only for 3 of the 6 currencies analysed can profits be made. Overall, the EMH is not contradicted.

The corresponding results for Strategy 2 are presented in Table 1b.

Table 1b: Summary of testing results for the Strategy 2

Type of a market	Totaltrades	Profittrades	Profittrades % oftotal	Totalnetprofit	Profittrades %>50%	Profit>0, %
US stock market	405	190	47%	-650	20%	34%
Russian stock market	329	149	45%	40	13%	25%
FOREX	724	358	49%	2738	33%	67%
GOLD	449	224	50%	15673	0%	100%

It appears that this strategy can be profitable in 3 of the 4 markets examined, especially in the FOREX and gold markets. However, the number of profitable trades is less than 50% in the stock market, specifically 34% and 25% using a single asset in the US (with only 12 out of 35 instruments generating profits) and Russian stock markets. The corresponding percentage for the FOREX is 67%, indicating the existence of a market anomaly in this case.

These results imply that Strategy 2 (Sell on Monday open. Close position on Monday close) is much more profitable than Strategy 1 (Sell on Friday close. Close position on Monday close). The implication is that the weekend effect cannot be attributed to the arrival of new information during weekends, and that the appropriate formulation for the weekend effect is “Mondays tend to generate negative returns”.

Given this mixed evidence, we also estimate the differencing parameter d for each day of the week under the three standard parameterisations of no deterministic terms, an intercept, and an intercept with a linear time trend. In the majority of cases, the lowest estimated value of d is found to be on Mondays (see Table B in the Appendix). The only two exceptions are the USDCHF and ALTRIA series, for which the lowest estimate corresponds to Friday and Wednesday respectively. However, this evidence is weak, since the unit root null hypothesis ($d = 1$) cannot be rejected in any case. The fact that the estimate of d is systematically smaller for Mondays than for the other days of the week suggests abnormal behaviour on this day. An estimated value of d significantly smaller than 1 would imply that it is possible to make systematic profits on this day of the week using historical data. However, as can be seen in the Appendix, the confidence intervals are relatively wide in all cases, and therefore the unit root null hypothesis cannot be rejected for any day of the week, which implies weak support for a weekend effect.

5. Conclusions

This paper examines one of the most recognized anomalies, i.e. the weekend effect, in various financial markets (US and Russian stock markets, FOREX, gold) applying two different methods to daily data. The first, the trading-bot approach, uses a trading robot to simulate the behaviour of traders according to a given algorithm (in our case trading on the weekend effect) and considering two alternative strategies. The second analyses the stochastic properties of the series on different days of the week by estimating their fractional integration parameter, testing if this value differs depending on the day of the week.

The results can be summarised as follows. Strategy 1 (Sell on Friday close. Close position on Monday close) is unprofitable in most cases. The only possible "weekend effect" formulation is "negative returns on Mondays". This is confirmed by the results for Strategy 2 (Sell on Monday open. Close position on Monday close): in this case it is possible to make profits, although the number of profitable deals is less than 50% and therefore it cannot be concluded that there is a market anomaly according to our criterion. The estimates of the fractional parameter d are lowest on Mondays in most cases, which is evidence in favour of the weekend effect, although the wide confidence intervals mean that this evidence is rather weak. Finally, exploitable profit opportunities based on the weekend effect are found mainly in the FOREX market.

References

Agrawal, A., Tandon, K., 1994, Anomalies or Illusions? Evidence from Stock Markets in Eighteen Countries. Journal of international Money and Finance, №13, 83-106.

Ariel, R., 1990, High Stock Returns Before Holidays: Existence and Evidence on Possible Causes. Journal of Finance, (December), 1611-1626.

Bloomfield, P. (1973).An exponential model in the spectrum of a scalar time series, *Biometrika* 60, 217-226.

Chen, H. and Singal, V., 2003, Role of Speculative Short Sales in Price Formation: The Case of the Weekend Effect. Journal of Finance. LVIII, 2.

Christophe, S., Ferri, M. and Angel, J., 2007, Short-selling and the Weekend Effect in Stock Returns http://www.efmaefm.org/0EFMAMEETINGS/EFMA%20ANNUAL%20MEETINGS/ 2007-Vienna/Papers/0260.pdf.

Connolly, R., 1989, An Examination of the Robustness of the Weekend Effect. Journal of Financial and Quantitative Analysis, 24, 2,133-169.

Cross, F., 1973, The Behavior of Stock Prices on Fridays and Mondays. Financial Analysts Journal, November - December, 67-69.

Fields, M., 1931, Stock Prices: A Problem in Verification. Journal of Business. October. 415-418.

Fortune, P., 1998, Weekends Can Be Rough : Revisiting the Weekend Effect in Stock Prices. Federal Reserve Bank of Boston. Working Paper No. 98-6.

Fortune, P., 1999, Are stock returns different over weekends? a jump diffusion analysis of the «weekend effect». New England Economic Review.3-19

French, K., 1980, Stock Returns and the Weekend Effect. Journal of Financial Economics. 8, 1, 55-69.

Gibbons, M. and Hess, P., 1981, Day Effects and Asset Returns. Journal of Business, 54, no, 4, 579-596.

Hsaio, P., Solt, M., 2004, Is the Weekend Effect Exploitable? Investment Management and Financial Innovations, 1, 53.

Kazemi, H. S., Zhai, W., He, J. and Cai, J., 2013, Stock Market Volatility, Speculative Short Sellers and Weekend Effect: International Evidence. Journal of Financial Risk Management. Vol.2 , No. 3. 47-54.

Keim, D. B. and R. F. Stambaugh, 1984, A Further Investigation of the Weekend Effect in Stock Returns, Journal of Finance, Vol. 39 (July), 819-835.

Olson, D., Chou, N. T., & Mossman, C., 2011, Stages in the Life of the Weekend Effect http://louisville.edu/research/for-faculty-staff/reference-search/1999-references/2011-business/olson-et-al-2011-stages-in-the-life-of-the-weekend-effect.

Racicot, F-É., 2011, Low-frequency components and the Weekend effect revisited: Evidence from Spectral Analysis. International Journal of Finance, 2, 2-19.

Rogalski, R. J., 1984, New Findings Regarding Day-of-the-Week Returns over Trading and Non-Trading Periods: A Note, Journal of Finance, Vol. 39, (December), 1603-1614.

Rystrom, D.S. and Benson, E., 1989, Investor psychology and the day-of-the-week effect. Financial Analysts Journal (September/October), 75-78.

Schwert, G. W., 2003, Anomalies and Market Efficiency. Handbook of the Economics of Finance. Elsevier Science B.V., Ch.5, 937-972.

Sias, R. W., Starks, L. T., 1995, The day-of-the week anomaly: the role of institutional investors. Financial Analyst Journal. May – June.58-67.

Singal, V. and Tayal, J. (2014) Does Unconstrained Short Selling Result in Unbiased Security Prices? Evidence from the Weekend Effect in Futures Markets (May 5, 2014). Available at SSRN: http://ssrn.com/abstract=2433233

Smirlock, M. and Starks, L., 1986, Day-of-the-Week and Intraday Effects in Stock Returns, Journal of Financial Economics, Vol. 17, 197-210.

APPENDIX

Table A1

US stock market, Strategy 1

Company	Total trades	Profit trades	Profit trades (% of total)	Total net profit	Profit per deal
Alcoa	442	206	47%	-379	-0.9
AltriaGroup	444	177	40%	-2518	-5.7
American Express Company	442	224	51%	747	1.7
AmericanInternationalGroupInc	444	205	46%	-1003	-2.3
ATT Inc	441	184	42%	-2253	-5.1
BankofAmerica	409	201	49%	1881	4.6
Boeing	444	212	48%	-2324	-5.2
CaterpillarInc	408	185	45%	-5631	-13.8
CISCO	409	187	46%	-1478	-3.6
Coca-Cola	445	184	41%	1009	2.3
DuPont	445	215	48%	-670	-1.5
ExxonMobilCorporation	445	200	45%	-3803	-8.5
Freeport-McMoRan Copper&GoldInc	409	207	51%	3711	9.1
Hewlett-Packard Company	412	194	47%	417	1.0
HomeDepotCorp	445	223	50%	-755	-1.7
HoneywellInternationalInc	445	218	49%	-685	-1.5
IntelCorporation	444	190	43%	-1778	-4.0
InternationalPaperCompany	445	213	48%	-832	-1.9
Johnson&Johnson	445	201	45%	-3261	-7.3
JP MorganChase	445	220	49%	2016	4.5
KraftFoods	410	166	40%	-2781	-6.8
McDonaldsCorporation	445	190	43%	-5021	-11.3
MerckCoInc	445	205	46%	-3812	-8.6
Microsoft	445	198	44%	-1365	-3.1
MMM Company	445	201	45%	-2364	-5.3
Pfizer	445	202	45%	-1409	-3.2
ProcterGambleCompany	445	198	44%	-3563	-8.0
QUALCOMM Inc	409	230	56%	2824	6.9
Travelers	409	189	46%	27,8	0.1
UnitedParcelServiceInc	409	175	43%	-4776	-11.7
United Technologies Corporation	445	209	47%	-4521	-10.2
VerizonCommunicationsInc	449	203	45%	-1059	-2.4
Wal-Mart StoresInc	445	200	45%	-3445	-7.7
WaltDisney	445	213	48%	-824	-1.9
Yahoo! Inc	406	215	53%	2977	7.3

Average	434	201	46%	-1334	-3

Table A2

US stock market, Strategy 2

Company	Total trades	Profit trades	Profit trades (% of total)	Total net profit	Profit per deal
Alcoa	412	204	50%	594	1.4
AltriaGroup	413	184	45%	-1389	-3.4
American Express Company	412	218	53%	1194	2.9
AmericanInternationalGroupInc	413	231	56%	1227	3.0
ATT Inc	410	182	44%	-1179	-2.9
BankofAmerica	384	204	53%	2840	7.4
Boeing	413	190	46%	-851	-2.1
CaterpillarInc	385	188	49%	78	0.2
CISCO	384	173	45%	-1091	-2.8
Coca-Cola	413	175	42%	-2691	-6.5
DuPont	413	180	44%	-594	-1.4
ExxonMobilCorporation	413	180	44%	-4024	-9.7
Freeport-McMoRan Copper&GoldInc	384	202	53%	7284	19.0
Hewlett-Packard Company	383	163	43%	-2305	-6.0
HomeDepotCorp	413	197	48%	-679	-1.6
HoneywellInternationalInc	413	200	48%	-190	-0.5
IntelCorporation	413	187	45%	-1137	-2.8
InternationalPaperCompany	413	206	50%	61	0.1
Johnson&Johnson	413	180	44%	-2377	-5.8
JP MorganChase	413	197	48%	2259	5.5
KraftFoods	382	174	46%	-1374	-3.6
McDonaldsCorporation	413	179	43%	-3537	-8.6
MerckCoInc	413	181	44%	-2268	-5.5
Microsoft	413	197	48%	-1165	-2.8
MMM Company	413	172	42%	-1977	-4.8
Pfizer	413	178	43%	-1185	-2.9
ProcterGambleCompany	413	173	42%	-3806	-9.2
QUALCOMM Inc	384	197	51%	1693	4.4
Travelers	384	185	48%	320	0.8
UnitedParcelServiceInc	384	161	42%	-3972	-10.3
United Technologies Corporation	413	201	49%	-2158	-5.2
VerizonCommunicationsInc	416	207	50%	140	0.3
Wal-Mart StoresInc	413	189	46%	-2782	-6.7
WaltDisney	413	208	50%	-5	0.0
Yahoo! Inc	383	211	55%	2311	6.0
Average	**405**	**190**	**47%**	**-650**	**-2**

Table A3

Russian stock market, Strategy 1

Company	Total trades	Profit trades	Profit trades (% of total)	Total net profit	Profit per deal
GAZPROM	335	153	46%	-81	-0.2
NORILSKY NICKEL	373	174	47%	-1540	-4.1
LUKOIL	393	190	48%	1857	4.7
ROSNEFT	218	98	45%	-117	-0.5
SBERBANK	365	158	43%	-1262	-3.5
GAZPROM NEFT	357	143	40%	-228	-0.6
SURGUTNEFTEGAZ	240	103	43%	-540	-2.3
VTB BANK	315	111	35%	-369	-1.2
Average	**325**	**141**	**43%**	**-285**	**-0.96**

Table A4

Russian stock market, Strategy 2

Company	Total trades	Profit trades	Profit trades (% of total)	Total net profit	Profit per deal
GAZPROM	325	135	42%	-345	-1.1
NORILSKY NICKEL	359	180	50%	1055	2.9
LUKOIL	376	186	49%	1295	3.4
ROSNEFT	210	89	42%	-200	-1.0
SBERBANK	352	171	49%	-257	-0.7
GAZPROM NEFT	345	141	41%	-321	-0.9
SURGUTNEFTEGAZ	359	168	47%	-657	-1.8
VTB BANK	306	120	39%	-254	-0.8
Average	**329**	**149**	**45%**	**40**	**0.01**

Table A5

FOREX, Strategy 1

Asset	Total trades	Profit trades	Profit trades (% of total)	Total net profit	Profit per deal
EURUSD	724	367	51%	25948	36
GBPUSD	724	364	50%	48839	67
USDCHF	724	334	46%	-17523	-24
USDJPY	724	370	51%	9807	14
AUDUSD	724	358	49%	-4671	-6
USDCAD	724	349	48%	-16044	-22
Average	**724**	**357**	**49%**	**7726**	**11**

TABLE A6

FOREX, Strategy 2

Asset	Total trades	Profit trades	Profit trades (% of total)	Total net profit	Profit per deal
EURUSD	724	363	50%	18640	26
GBPUSD	724	360	50%	20576	28
USDCHF	724	355	49%	-16479	-23
USDJPY	724	377	52%	6281	9
AUDUSD	724	337	47%	554	1
USDCAD	724	357	49%	-13142	-18
Average	**724**	**358**	**49%**	**2738**	**4**

TABLE A7

Gold, Strategy 1

Asset	Total trades	Profit trades	Profit trades (% of total)	Total net profit	Profit per deal
Gold	453	210	46%	-18733	-41

TABLE A8

Gold, Strategy 2

Asset	Total trades	Profit trades	Profit trades (% of total)	Total net profit	Profit per deal
Gold	449	224	50%	15673	35

Estimates of d in a model with autocorrelated errors

Table B1: Estimates of d in a model with autocorrelated errors: GOLD

Day of the week	No regressors	An intercept	A linear time trend
Monday	**0.930 (0.855, 1.064)**	**0.939 (0.866, 1.032)**	**0.939 (0.865, 1.035)**
Tuesday	0.930 (0.854, 1.047)	0.942 (0.871, 1.044)	0.942 (0.877, 1.042)
Wednesday	0.938 (0.841, 1.064)	0.949 (0.872, 1.062)	0.950 (0.876, 1.068)
Thursday	0.937 (0.843, 1.055)	0.946 (0.866, 1.053)	0.946 (0.864, 1.057)
Friday	0.936 (0.840, 1.060)	0.943 (0.865, 1.054)	0.943 (0.863, 1.057)

Table B2: Estimates of d in a model with autocorrelated errors: EURUSD

Day of the week	No regressors	An intercept	A linear time trend
Monday	**0.954 (0.877, 1.044)**	**0.963 (0.885, 1.066)**	**0.963 (0.885, 1.063)**
Tuesday	0.958 (0.884, 1.037)	0.991 (0.900, 1.092)	0.992 (0.902, 1.092)
Wednesday	0.961 (0.886, 1.055)	1.010 (0.921, 1.107)	1.010 (0.924, 1.107)
Thursday	0.964 (0.876, 1.045)	1.008 (0.936, 1.106)	1.008 (0.935, 1.106)
Friday	0.972 (0.890, 1.050)	1.003 (0.914, 1.104)	1.003 (0.914, 1.098)

Table B3: Estimates of d in a model with autocorrelated errors: USDCHF

Day of the week	No regressors	An intercept	A linear time trend
Monday	1.008 (0.940, 1.104)	0.936 (0.856, 1.042)	0.936 (0.856, 1.045)
Tuesday	1.016 (0.945, 1.117)	0.937 (0.857, 1.044)	0.936 (0.857, 1.042)
Wednesday	1.012 (0.941, 1.113)	0.929 (0.853, 1.030)	0.929 (0.842, 1.032)
Thursday	1.015 (0.931, 1.098)	0.930 (0.843, 1.013)	0.930 (0.846, 1.012)
Friday	**1.002 (0.920, 1.089)**	**0.928 (0.850, 1.034)**	**0.928 (0.843, 1.034)**

Table B4: Estimates of d in a model with autocorrelated errors: LUKOIL

Day of the week	No regressors	An intercept	A linear time trend
Monday	**0.987 (0.888, 1.118)**	**0.858 (0.736, 1.035)**	**0.858 (0.734, 1.035)**
Tuesday	0.989 (0.882, 1.155)	0.859 (0.739, 0.978)	0.859 (0.739, 0.977)
Wednesday	0.934 (0.837, 1.059)	0.868 (0.752, 1.024)	0.868 (0.752, 1.019)
Thursday	1.007 (0.883, 1.143)	0.927 (0.793, 1.073)	0.921 (0.802, 1.075)
Friday	1.002 (0.905, 1.136)	0.898 (0.767, 1.057)	0.898 (0.776, 1.055)

Table B5: Estimates of d in a model with autocorrelated errors: GAZPROM

Day of the week	No regressors	An intercept	A linear time trend
Monday	**0.939 (0.820, 1.184)**	**0.963 (0.836, 1.102)**	**0.963 (0.836, 1.102)**
Tuesday	0.962 (0.845, 1.107)	0.992 (0.857, 1.144)	0.992 (0.855, 1.142)
Wednesday	0.954 (0.841, 1.100)	0.982 (0.863, 1.130)	0.982 (0.863, 1.132)
Thursday	0.962 (0.831, 1.118)	0.997 (0.863, 1.155)	0.997 (0.862, 1.155)
Friday	0.939 (0.877, 1.089)	0.987 (0.860, 1.131)	0.988 (0.861, 1.132)

Table B6: Estimates of d in a model with autocorrelated errors: ALTRIA

Day of the week	No regressors	An intercept	A linear time trend
Monday	1.005 (0.910, 1.122)	1.008 (0.916, 1.132)	1.007 (0.915, 1.133)
Tuesday	0.993 (0.925, 1.097)	0.992 (0.907, 1.094)	0.992 (0.907, 1.096)
Wednesday	**0.986 (0.911, 1.090)**	**0.971 (0.883, 1.076)**	**0.971 (0.883, 1.076)**
Thursday	0.986 (0.913, 1.103)	0.979 (0.903, 1.085)	0.979 (0.903, 1.086)
Friday	1.001 (0.917, 1.093)	0.991 (0.900, 1.091)	0.994 (0.900, 1.091)

Table B7: Estimates of d in a model with autocorrelated errors: FREEPORT

Day of the week	No regressors	An intercept	A linear time trend
Monday	**1.042 (0.944, 1.183)**	**1.047 (0.944, 1.183)**	**1.047 (0.943, 1.190)**
Tuesday	1.096 (0.984, 1.232)	1.050 (0.990, 1.255)	1.064 (0.990, 1.255)
Wednesday	1.074 (0.960, 1.210)	1.073 (0.962, 1.204)	1.072 (0.960, 1.204)
Thursday	1.044 (0.943, 1.199)	1.044 (0.943, 1.179)	1.049 (0.943, 1.179)
Friday	1.067 (0.967, 1.221)	1.088 (0.962, 1.224)	1.088 (0.962, 1.225)