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The Frequency of One-Day Abnormal Returns and Price Fluctuations in the FOREX

Abstract

This paper analyses the explanatory power of the frequency of abnormal returns in the FOREX for the EURUSD, GBRUSD, USDJPY, EURJPY, GBPCHF, AUDUSD and USDCAD exchange rates over the period 1994-2019. Abnormal returns are detected using a dynamic trigger approach; then the following hypotheses are tested: their frequency is a significant driver of price movements (H1); it does not exhibit seasonal patterns (H2); it is stable over time (H3). For our purposes a variety of statistical methods (both parametric and non-parametric) are applied including ADF tests, Granger causality tests, correlation analysis, (multiple) regression analysis, Probit and Logit regression models. No evidence is found of either seasonal patterns or instability. However, there appears to be a strong positive (negative) relationship between returns in the FOREX and the frequency of positive (negative) abnormal returns. On the whole, the results suggest that the latter is an important driver of price dynamics in the FOREX, is informative about crises and can be the basis of profitable trading strategies, which is inconsistent with market efficiency.

JEL-Codes: G120, G170, C630.

Keywords: FOREX, anomalies, price dynamics, frequency of abnormal returns.

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1. Introduction

The FOREX is one of the most liquid (with $6 tn daily turnover) and efficient financial markets (Oh et al., 2006; Serbinenko and Rachev, 2009, Kallianiotis, 2017). Nevertheless, several studies have attempted to detect anomalies in the behaviour of exchange rates such as abnormal returns with the associated contrarian or momentum patterns (Parikakis and Syriopoulos, 2008; Caporale et al., 2018), and also investigated whether they can be used as an early warning indicators for financial crises (e.g., the East Asian and the Russian crises of the 1990s, the Dotcom bubble of 1997-2001, and the global financial crisis of 2007-8). The various methods used include price trends and persistence analysis, trade volumes and price volatility analysis, correlation between assets etc. (Granger and Newbold, 1986; Bremer et al, 1997; Eross et al, 2019).

The present paper takes instead a different approach to analyse the explanatory power of the frequency of abnormal returns; this issue has been previously examined in the case of stock markets (Angelovska, 2016; Caporale and Plastun, 2019) and cryptocurrency markets (Caporale et al., 2019), but not in that of the FOREX, which is the focus of this study.

Abnormal returns are detected using a dynamic trigger approach. Then the following hypotheses are tested: (i) their frequency is a significant driver of price movements (H1); (ii) it does not exhibit seasonal patterns (H2); (iii) it is stable over time (H3). For our purposes a variety of statistical methods (both parametric and non-parametric) are applied including ADF tests, Granger causality tests, correlation analysis, (multiple) regression analysis, Probit and Logit regression models.

The remainder of the paper is organised as follows. Section 2 contains a brief review of the relevant literature. Section 3 describes the methodology. Section 4 discusses the empirical results. Section 5 offers some concluding remarks.

2. Literature Review

There exists an extensive literature investigating one-day abnormal price changes. Various explanations have been suggested for their occurrence. For instance, Govindaraj et al. (2014) and Jin et al. (2012) examined the role of new information, noise or liquidity trades. Bartos (2015) argued that new information is immediately absorbed without significant price effects. The most popular explanations rely on cognitive traps and biases (Barberis, Shleifer and Vishny, 1998), as well as emotions and psychological aspects of trading and investment (Daniel et al., 1998, Griffin and Tversky, 1992; Madura and Richie, 2004). Aiyagari and Gertler (1999) and Hong and Stein (1999) see their roots in the presence and activity of "noise" traders. Duran and Caginalp (2007) argued that abnormal returns result from the use of technical and fundamental analysis by investors for decision-making. Other studies have considered the impact of market liquidity (Jegadeesh and Titman, 1993), news (Kocenda and Moravcova, 2018) etc.

Abnormal price changes can generate different price patterns. Atkins and Dyl (1990) and Bremer et al. (1997) found contrarian effects (price reversals) after large price changes. By contrast, Cox and Peterson (1994) did not detect a negative correlation between abnormal returns on the day prices fall and the following three days. Schnusenberg and Madura (2001) and Lasfer et al. (2003) provided evidence of momentum effects. Savor (2012) and Govindaraj et al. (2014) found both effects in the US stock market (momentum effects when analysts issue revisions or price reversals after large daily price shocks).

Various other studies also analyse some of the implications of abnormal returns. For instance, Pritamani and Singhal (2001) showed that information about large price changes can be used to design profitable trading strategies. Govindaraj et al. (2014) also found that a trading strategy based on these effects can generate significant excess returns. Similar conclusions were reached by Caporale et al. (2018), who tested price effects after abnormal price returns in different financial markets; they showed that the reversal effect is exploitable in the stock market, whilst the momentum effect produces profits in the case of the FOREX and commodity markets. By contrast, Cox and Peterson (1994) and Lasfer at al. (2003) argued that trading strategies based on price patterns after one-day abnormal returns can hardly be profitable because of the presence of trading costs and the relatively small size of price reversals. According to Sandoval and Franca (2012), abnormal price changes can also be informative about future price movements and be used as a crisis identifier.

Typically abnormal returns are analysed in the case of stock markets (Atkins and Dyl, 1990; Cox and Peterson, 1994; Bremer et al. 1997; Govindaraj et al., 2014; Sandoval and Franca, 2012; Angelovska, 2016 and many others) or cryptocurrency markets; in particular, Caporale and Plastun (2019) and Caporale et al. (2019) showed that the frequency of abnormal returns can provide useful information in the case of the cryptocurrency markets. Much less evidence is available for the FOREX, which is the focus of the present paper. An exception is the study carried out by Parikakis and Syriopoulos (2008), who investigated patterns following excess one-day fluctuations for various currencies and found that a contrarian strategy is profitable in the FOREX.

3. Methodology

To analyse the frequency of abnormal returns and their role as drivers of price dynamics we use daily and monthly data for the main exchange rates, specifically for EURUSD, GBRUSD, USDJPY, EURJPY, GBPCHF, AUDUSD and USDCAD over the period 03.01.1994-28.05.2019; the data source is Yahoo! Finance (https://finance.yahoo.com).

There are two main approaches to detecting abnormal returns, namely a static one (which uses a specific threshold as an abnormal price criterion, as in Bremer and Sweeney, 1991) and a dynamic one (which is based on relative values – normally abnormal returns are defined on the basis of the number of standard deviations to be added to the average return as in Caporale and Plastun, 2018). Since they can perform rather differently depending on the dataset (Caporale et al., 2018) the first step is to choose the most appropriate method for the data in hand.

Let returns be defined as:

$$R_t = P_t / P_{t-1} \tag{1}$$

where R_t stands for returns, and P_t and P_{t-1} are the close prices of the current and previous day. The static approach introduced by Sandoval and Franca (2012) and developed by Caporale and Plastun (2019) is based on creating histograms with values 10% above or below those of the population; thresholds are then obtained for both positive and negative abnormal returns, and periods can be identified when returns were above or equal to the threshold.

In the dynamic trigger approach (Wong, 1997; Caporale et al., 2018) abnormal price changes are defined by the following inequality:

$$R_i > (\overline{R}_n + k \times \delta_n) \tag{2}$$

and negative abnormal price change are defined as:

$$R_i < (\overline{R}_n - k \times \delta_n) \tag{3}$$

where k is the number of standard deviations used to identify them (specifically, k=1), $\overline{R}_n$ is the average size of daily returns for period n and δ_n is the standard deviation of daily returns for period n

Both procedures (static and dynamic) generate a data set for the frequency of abnormal returns (at a monthly frequency), which is then divided into 4 subsets including respectively the frequency of negative and positive abnormal returns, the difference between them and the overall frequency of abnormal returns (positive as well as negative).

Then the following hypotheses are tested:

(i) the frequency of abnormal returns is a significant driver of price movements (H1),
(ii) it does not exhibit seasonal patterns (H2),
(iii) it is stable over time (H3).

To test H1, we regress monthly returns (and any observed momentum or contrarian effects) against the frequency of abnormal returns over a 1-month period; specifically we estimate the following regressions:

$$\mathrm{Y_t} = \mathrm{a_0} + \mathrm{a_1}\ \mathrm{F_t^+} + \mathrm{a_2}\ \mathrm{F_t^-} + \varepsilon_\mathrm{t} \qquad (4)$$

where Y_t – returns on day *t;*

$\mathrm{a_0}$–mean return;

a_1 (a_2) – coefficients on the frequency of positive and negative abnormal returns respectively;

$\mathrm{F_t^+}$ ($\mathrm{F_t^-}$) – the number of positive (negative) abnormal returns days during a period *t*;

ε_t – Random error term at time *t*.

$$\mathrm{Y_t} = \mathrm{a_0} + \mathrm{a_1}\ \mathrm{F_t^{delta}} + \varepsilon_\mathrm{t} \qquad (5)$$

where Y_t – returns on day *t;*

$\mathrm{a_0}$–mean return;

a_1 – coefficient on the delta frequency;

$\mathrm{F_t^{delta}}$– the difference between the number of positive (negative) abnormal returns days during a period *t*;

ε_t – Random error term at time *t*.

As an alternative, Logit and Probit regressions are run. These are binary choice models producing estimates of the probability that the dependent variable will take the value 1 depending on the values of the regressors. In a Logit regression, it is assumed that the probability of event y being equal to 1 is given by $P\{y=1|x\} = f(z)$, where $f(z) = \frac{1}{1-\exp(-z)}$ - is the logistic function, and the parameter z is determined on the basis of regression (6).

$$z_t = a_0 + a_1\, O_t^+ + a_2\, O_t^- + \varepsilon_t \qquad (6)$$

where z_t is a binary value equal to 1 if the return on day *t* increased compared to day *t-1*; otherwise, this value is 0.

a_0– constant;

a_1 (a_2) – coefficients on positive and negative abnormal returns respectively;

F_t^+ (F_t^-) – the number of positive (negative) abnormal returns days during a period *t*;

ε_t – Random error term at time *t*.

If the probability predicted by the model $P(x) > 0.5$, then the dependent variable is equal to 1, whilst $P(x) \le 0.5$ - implies that it is equal to 0. The Probit regression is based on the assumption that the variable under investigation is normally distributed.

The size, sign and statistical significance of the coefficients provide information about the possible effects of the frequency of abnormal returns on returns in the FOREX. A number of diagnostic tests are also carried out; these include Lilliefors's test, Durbin–Watson's test, White's test, Ramsey's Regression Equation Specification Error Test (RESET) and Chow's test. Table 1 specifies the null hypothesis in each case.

Table 1: Diagnostic Tests

Tests	Null hypothesis
Lilliefors's test	Normal distribution
Durbin–Watson's test	No autocorrelation
White's test	No heteroscedasticity
Ramsey's Regression Equation Specification Error Tes t (RESET)	Adequate functional form
Chow's test	No structural change

To test H2 and H3 we perform both parametric (ANOVA analysis) and non-parametric (Kruskal-Wallis) tests.

4. Empirical Results

As a first step, one needs to choose between the static and dynamic approaches to calculate abnormal returns. For this purpose the EURUSD exchange rate is used. Table 2 reports the correlation coefficients between the two sets of results.

Table 2: Correlation analysis of data from the static and dynamic approaches

Data	Frequency of negative abnormal returns	Frequency of positive abnormal returns	Frequency delta	Overall frequency of abnormal returns
Correlation between data on static and dynamic approaches	0.46	0.54	0.74	0.33

As can be seen, in the case of the frequency delta parameter the correlation is rather high; however, the other correlation coefficients imply a sizeable difference between the static and dynamic results. To choose between the two, we focus on the correlation between the frequency of abnormal returns and both close prices and returns. The results are reported in Table 3.

Table 3: Correlation analysis of data from the static and dynamic approaches

Approach	Dynamic		Static	
Parameter/Price data	Close	Returns	Close	Returns
Frequency of negative abnormal returns	0.01	-0.56	-0.07	-0.47
Frequency of positive abnormal returns	0.04	0.59	-0.04	0.41
Frequency delta	0.02	0.76	0.03	0.79
Overall frequency of abnormal returns	0.04	-0.01	-0.07	-0.05

As can be seen the frequency of abnormal returns is correlated only with monthly returns, and consequently only these will be used to test the hypotheses of interest; further, the dynamic approach produces higher correlations for the frequency of negative and positive abnormal returns, and therefore will be used in the remainder of the analysis to detect abnormal returns. Finally, since the overall frequency of abnormal returns does not appear to be informative about price dynamics, only the frequency of negative and positive abnormal returns, and the frequency delta, will be used.

ADF tests (Dickey and Fuller, 1979) carried out on the series of interest (see Appendix C, Tables C.1-C.7) imply a rejection of the unit root null in all cases (i.e., stationarity). Table 4 reports the correlation coefficients for the number of negative and positive abnormal returns, as well as the frequency delta between the number of positive and negative abnormal returns and monthly returns.

Table 4: Correlation coefficients between the frequency of abnormal returns and monthly returns

Parameter	EURUSD	GBPUSD	USDJPY	USDCAD	AUDUSD	EURJPY	GBPCHF
Frequency of negative abnormal returns	-0.56	-0.61	-0.57	-0.46	-0.63	-0.57	-0.59
Frequency of positive abnormal returns	0.59	0.49	0.50	0.61	0.38	0.36	0.33
Frequency delta	0.76	0.74	0.73	0.72	0.70	0.71	0.66

As can be seen, there is negative (positive) correlation between the frequency of negative (positive) abnormal returns and price dynamics in the FOREX, and the frequency delta has the highest (positive) correlation coefficient, which implies that this variable is the most informative about price movements.

As a further check, we carry out cross-correlation analysis also at the time intervals t and $t+i$, where $I \in \{-10, . . . , 10\}$. Figures D.1-D.7 reports the cross-correlation between returns and the frequency of (both positive and negative) abnormal returns for the whole sample period for different leads and lags. The highest coefficient corresponds to lag length zero, which means that there is no need to shift the data.

Additional evidence is provided by Granger causality tests (Granger, 1969) between returns in the FOREX and the frequency of abnormal returns (both positive and negative, and also for their delta). The results are presented in Appendix G, Table G.1. As can be seen, the null hypothesis of no causality cannot be rejected in any case (the single exception is USDJPY).

The next step is to test H1 by running a number of simple linear regressions for returns against the frequency of negative and positive abnormal returns and the delta frequency, as well as regressions with dummy variables (see Section 3 for details). The results are presented in Appendix E, Tables E.1-E.7. As can be seen, all the regressors are statistically significant. Both actual and estimated values are plotted in Figures H.1-H.7. The latter appear to capture well the behaviour of the former. Various diagnostic tests for the models from Tables E.1-E.7 are reported in Table 5, and suggest that the estimated models have the appropriate functional form and their residuals are not autocorrelated. The model for the EURUSD exchange rate passes all tests, but there is evidence of non-normality of the residuals in the case of EURJPY, USDJPY, GBPCHF, and both heteroscedasticity of residuals and unstable parameters are present in the models for GBRUSD, AUDUSD and USDCAD.

Table 5: Diagnostic Tests for the Linear Regression Models

Parameter	EURUSD	GBRUSD	EURJPY	USDJPY	GBPCHF	AUDUSD	USDCAD
Lilliefors's test							
L- statistics	0.0360	0.0521	0.0581	0.0593	0.0728	0.0488	0.0468
p-value	0.44	0.05	0.02	0.01	0.00	0.08	0.11
null hypothesis	not rejected	not rejected	rejected	rejected	rejected	not rejected	not rejected
Durbin–Watson's test							
DW	1.9737	1.8693	1.9826	2.1035	2.2733	1.8577	2.0776
p-value	0.4125	0.1309	0.4435	0.8168	0.9914	0.1098	0.7688
null hypothesis	not rejected	not rejected	not rejected	not rejected	not rejected	not rejected	not rejected
White's test							
LM- statistics	7.7284	32.6237	22.6733	4.0720	2.6464	23.7661	47.7710
p-value	0.1718	0.0000	0.0004	0.5390	0.7542	0.0002	0.0000
null hypothesis	not rejected	rejected	rejected	not rejected	not rejected	rejected	rejected
Ramsey's RESET							
F- statistics	1.9172	0.4110	2.2528	0.6896	1.0326	0.3250	1.5919
p-value	0.1488	0.663	0.1069	0.503	0.357	0.7227	0.205
null hypothesis	not rejected	not rejected	not rejected	not rejected	not rejected	not rejected	not rejected
Chow's test							
F- statistics	1.2255	3.3407	2.4515	2.9437	1.2567	5.2061	9.1103
p-value	0.3006	0.0197	0.0635	0.0333	0.2894	0.0016	0.0000
null hypothesis	not rejected	rejected	not rejected	rejected	not rejected	rejected	rejected

The best specifications for the linear regression models with the frequency of positive and negative abnormal returns as regressors (as indicated by the R-square for the whole model and the p-values for the estimated coefficients) are presented in Table 6.

Table 6: Best regression models for returns in the FOREX

Instrument	Regression with dummy variables
EURUSD	$return_{\mathrm{i}} = -0.0035 - 0.0101 \times \mathrm{F}_{\mathrm{i}}^{-} \quad + 0.0119 \times \mathrm{F}_{\mathrm{i}}^{+}$
GBPUSD	$return_{\mathrm{i}} = 0.0029 - 0.0102 \times \mathrm{F}_{\mathrm{i}}^{-} \quad + 0.0079 \times \mathrm{F}_{\mathrm{i}}^{+}$
USDJPY	$return_{\mathrm{i}} = 0.0025 - 0.0123 \times \mathrm{F}_{\mathrm{i}}^{-} \quad + 0.0109 \times \mathrm{F}_{\mathrm{i}}^{+}$
USDCAD	$return_{\mathrm{i}} = -0.0050 - 0.0076 \times \mathrm{F}_{\mathrm{i}}^{-} \quad + 0.0104 \times \mathrm{F}_{\mathrm{i}}^{+}$

AUDUSD	$return_i = 0.0130 - 0.0146 \times F_i^- \quad + 0.0093 \times F_i^+$
EURJPY	$return_i = 0.0069 - 0.0144 \times F_i^- \quad + 0.0117 \times F_i^+$
GBPCHF	$return_i = 0.0072 - 0.0115 \times F_i^- \quad + 0.0078 \times F_i^+$

* F_i^+ (F_i^-) – frequency of positive (negative) abnormal returns during a period *i*;

The Logit and Probit regression results for price closes are presented in Appendix F, Tables F.1-F.7. We find that the explanatory power of these models ranges between 73.9% and 76.3%. On the whole, the evidence supports H1.

Concerning H2, namely the possible presence of seasonal patterns in in the frequency of abnormal returns, at first we do some visual inspection of the data. Figure 1 displays positive and negative abnormal returns and the delta frequency by month for EURUSD and provides no prima facie evidence of seasonality for the former two, while the latter appears to be negative in January and May and positive in December. Further evidence of seasonal behaviour for the delta frequency is provided by Figure 2, which shows it for all the exchange rates considered.

Figure 1: The frequency of abnormal returns by month: the case of EURUSD

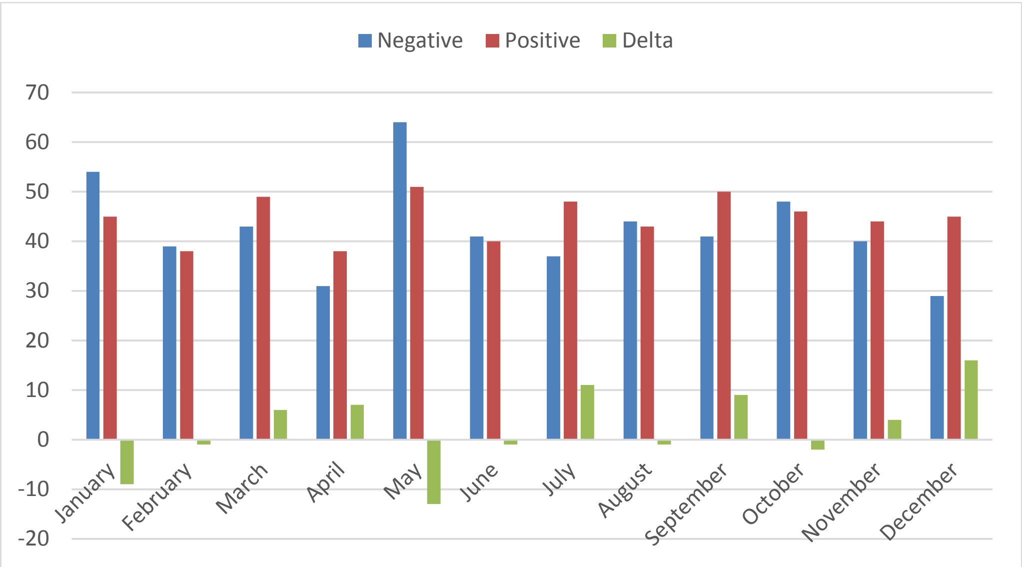
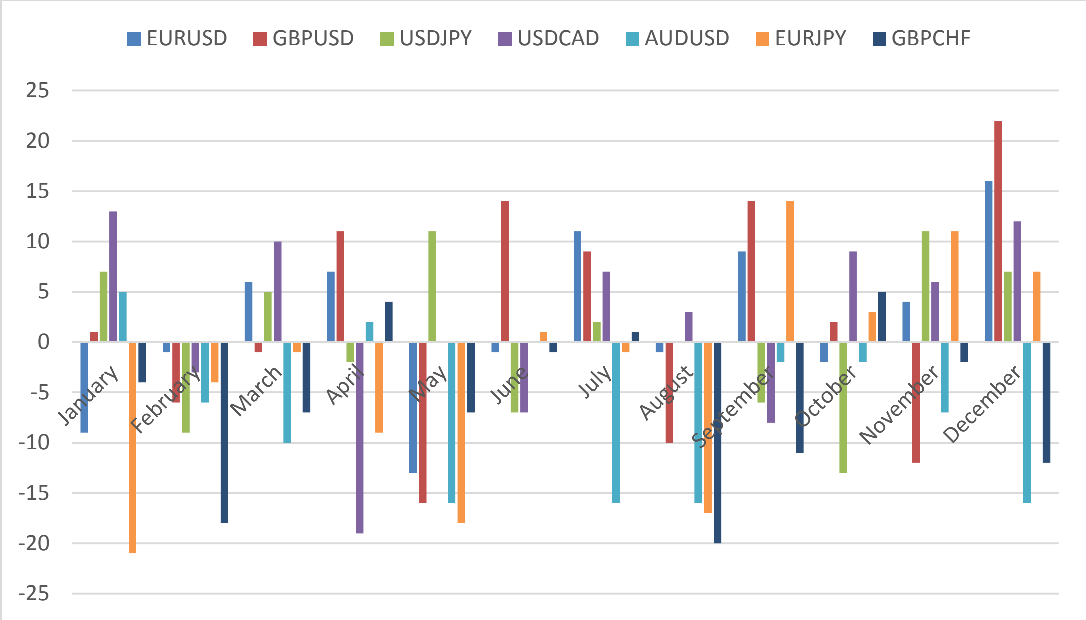


Figure 2: The delta frequency parameter by month



To see whether these seasonal differences are statistically significant we carry out ANOVA analysis and Kruskal-Wallis tests. The results at the 5% confidence level are reported in Table 7 and suggest that in most cases there are no significant seasonal patterns, which implies a rejection of H2.

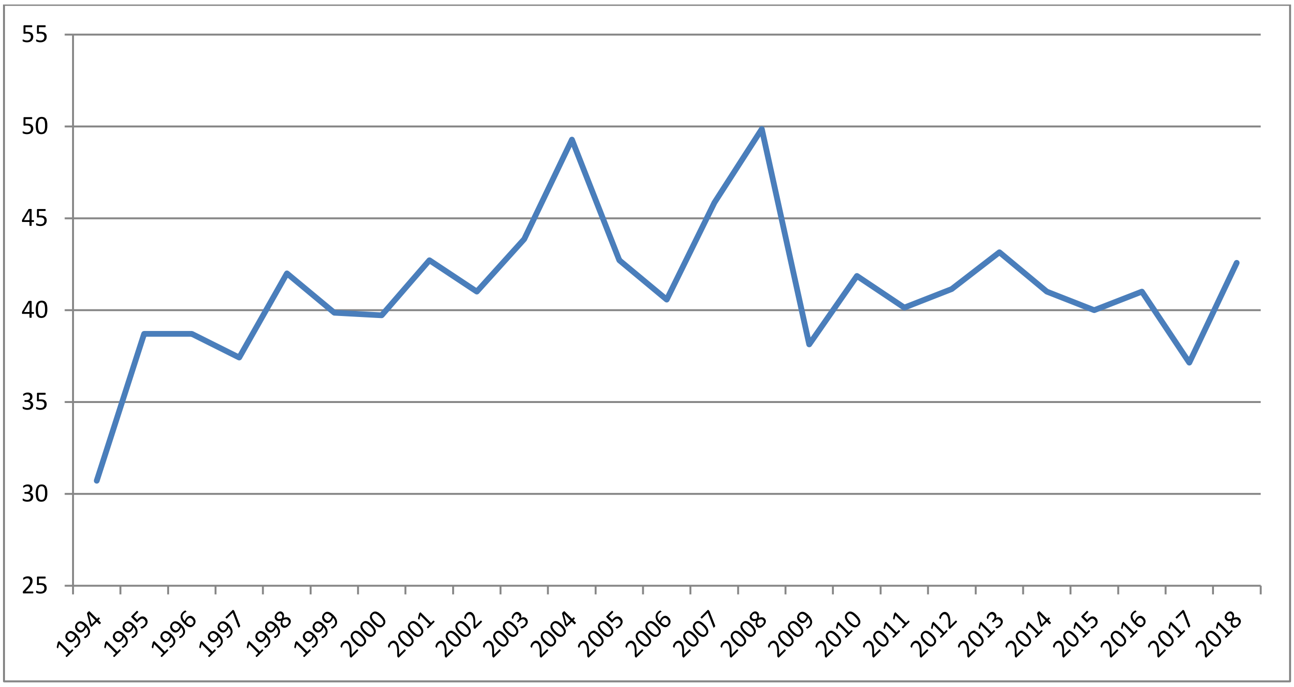
Table 7: Results of ANOVA and non-parametric Kruskal-Wallis tests for statistical differences in the frequency of abnormal returns between different months

Instrument	Parameter	ANOVA test			Kruskal-Wallis test		
		F-statistics	p-value	Null hypothesis	Chi Squared test	p-value	Null hypothesis
EURUSD	Returns	1.648	0.0851	not rejected	13.8977	0.2387	not rejected
	All_over	2.542	0.0044	rejected	25.026	0.0090	rejected
	Over_negative	2.525	0.0047	rejected	19.550	0.0519	not rejected
	Over_positive	0.556	0.8638	not rejected	6.8833	0.8084	not rejected
GBRUSD	Returns	1.733	0.0658	not rejected	26.521	0.0054	rejected
	All_over	2.678	0.0027	rejected	28.368	0.0028	rejected
	Over_negative	3.146	0.0005	rejected	35.185	0.0002	rejected
	Over_positive	1.369	0.1870	not rejected	15.246	0.1715	not rejected
EURJPY	Returns	1.290	0.2293	not rejected	11.817	0.3775	not rejected
	All_over	2.128	0.0185	rejected	22.608	0.0201	rejected
	Over_negative	2.355	0.0086	rejected	24.670	0.0102	rejected
	Over_positive	1.729	0.0667	not rejected	18.885	0.0632	not rejected
USDJPY	Returns	0.635	0.7985	not rejected	8.388	0.6782	not rejected
	All_over	2.211	0.0140	rejected	20.198	0.0427	rejected
	Over_negative	0.919	0.5226	not rejected	12.713	0.3125	not rejected
	Over_positive	2.056	0.0235	rejected	19.827	0.0478	rejected
GBPCHF	Returns	1.391	0.1763	not rejected	18.865	0.0636	not rejected

	All_over	0.858	0.5826	not rejected	11.571	0.3967	not rejected
	Over_negative	0.788	0.6518	not rejected	12.439	0.3316	not rejected
	Over_positive	1.039	0.4115	not rejected	13.749	0.2472	not rejected
AUDUSD	Returns	0.982	0.4630	not rejected	13.627	0.2543	not rejected
	All_over	3.248	0.0003	rejected	34.741	0.0003	rejected
	Over_negative	1.226	0.2692	not rejected	14.342	0.2146	not rejected
	Over_positive	2.853	0.0014	rejected	29.822	0.0017	rejected
USDCAD	Returns	1.119	0.3455	not rejected	16.630	0.1193	not rejected
	All_over	2.070	0.0225	rejected	18.512	0.0704	not rejected
	Over_negative	1.716	0.0694	not rejected	20.054	0.0446	rejected
	Over_positive	1.370	0.1863	not rejected	12.149	0.3525	not rejected

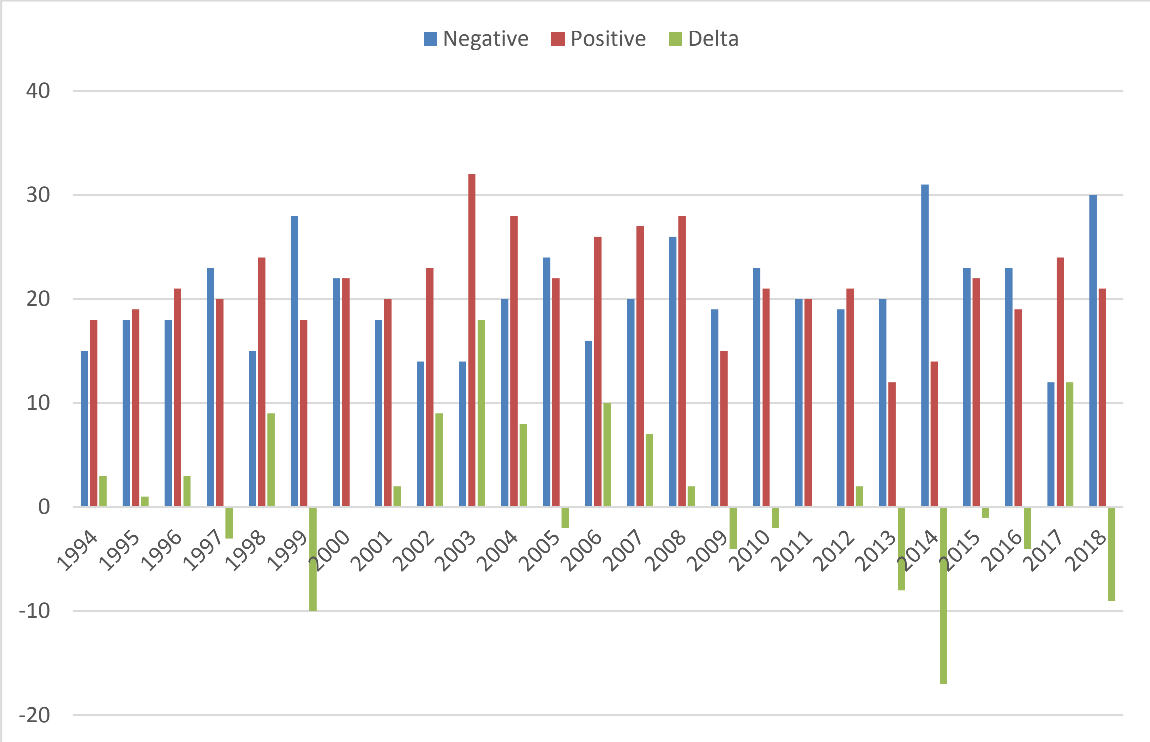
As for H3 (parameter stability), first we compute the average number of abnormal returns per year (positive+negative) based on all exchange rates considered; this is displayed in Figure 3. As can be seen, it was lower in the 1990s, and peaked in 2004 and 2008, the latter date coinciding with the global financial crisis.

Figure 3: Average frequency of abnormal returns (positive + negative) per year



More detailed evidence is presented in the case of EURUSD in Figure 4, which suggests the presence of time variation.

Figure 4: The frequency of abnormal (positive and negative returns) and the delta frequency by year: the case of EURUSD



The results of the ANOVA analysis and Kruskal-Wallis tests are reported in Table 8 and imply parameter stability, i.e. H3 cannot be rejected.

Table 8: Results of ANOVA and non-parametric Kruskal-Wallis tests for statistical differences in the frequency of overreactions between different years: the case of EURUSD

Parameter	**ANOVA test**			**Kruskal-Wallis test**		
	F-statistics	p-value	Null hypothesis	Chi Squared test	p-value	Null hypothesis
Delta	1.3480	0.1323	not rejected	23.6846	0.2085	not rejected
Negative	1.1096	0.3322	not rejected	16.5135	0.6228	not rejected
Positive	1.1145	0.3268	not rejected	25.4415	0.1465	not rejected

5. Conclusions

This paper investigates the explanatory power of the frequency of one-day abnormal returns in the FOREX for the cases of EURUSD, GBRUSD, USDJPY, EURJPY, GBPCHF, AUDUSD and USDCAD over the period 1994-2019. Using a dynamic trigger approach 4 series are created, specifically the frequency of negative and positive abnormal returns, the difference between the two and the overall frequency of abnormal returns. Then the following hypotheses are tested using a variety of parametric and non-parametric methods: the frequency of abnormal returns is a significant driver of price movements (H1); it does not exhibit seasonal patterns (H2); it is stable over time (H3).

The main findings can be summarised as follows. The frequency of abnormal returns in FOREX has significant explanatory power for returns, is informative about crises (since it increases sharply at the time of a crisis), is not seasonal, and is stable over time. On the whole, our findings suggest that profitable FOREX trading strategies can be designed based on the frequency of abnormal returns, which is evidence of market inefficiency. The difference between actual and estimated returns can be seen as an indication of whether currencies are over- or under-valued and therefore a price increase or decrease should be expected. Obviously currencies should be bought in the case of undervaluation and sold in the case of overvaluation till the divergence between actual and estimated values disappears, at which stage positions should be closed.

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Appendix A

Frequency distribution in the FOREX

TableA.1: Frequency distribution in the FOREX, 1994-2019

Plot	Frequency						
	EURUSD	GBPUSD	USDJPY	USDCAD	AUDUSD	EURJPY	GBPCHF
<-0,025	6	8	33	4	31	31	10
-0,02	13	14	20	7	41	51	18
-0,015	68	35	70	32	85	95	58
-0,01	249	171	239	143	323	280	201
-0,005	820	736	791	649	843	788	766
0	2096	2317	2090	2459	1828	1821	2143
0,005	2155	2259	2030	2464	2031	1997	2241
0,01	792	768	859	600	940	858	805
0,015	253	191	246	131	279	274	177
0,02	66	31	68	32	82	93	32
0,025	15	10	21	14	28	31	22
>0,025	11	2	15	9	23	22	11

This table presents estimates of the frequency distribution for returns in FOREX (selected assets) over the period 01.01.1994-31.05.2019. The first column reports the values for FOREX returns, the other columns the corresponding frequency.

Figure A.1: Frequency distribution of EURUSD, 1994-2019

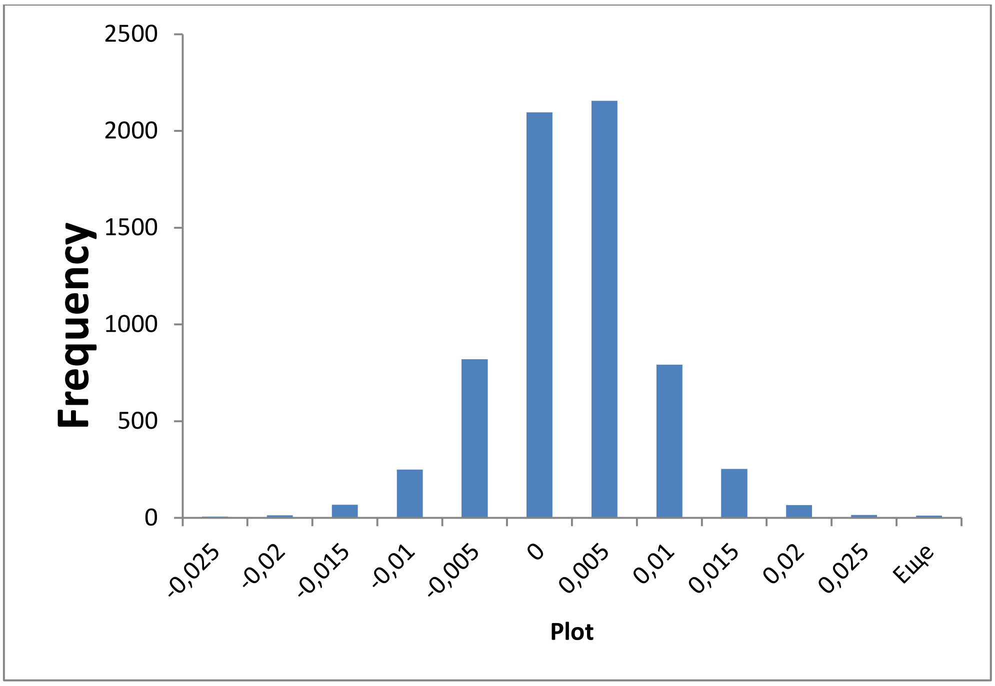


Figure A.2: Frequency distribution of GBPUSD, 1994-2019

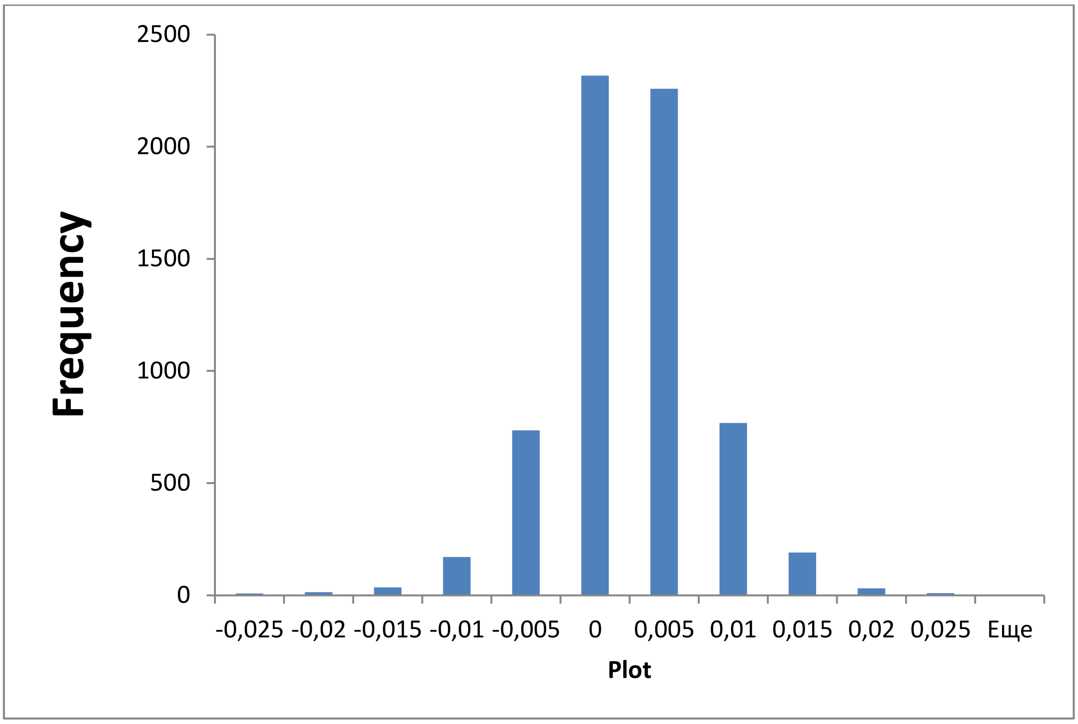


Figure A.3: Frequency distribution of USDJPY, 1994-2019

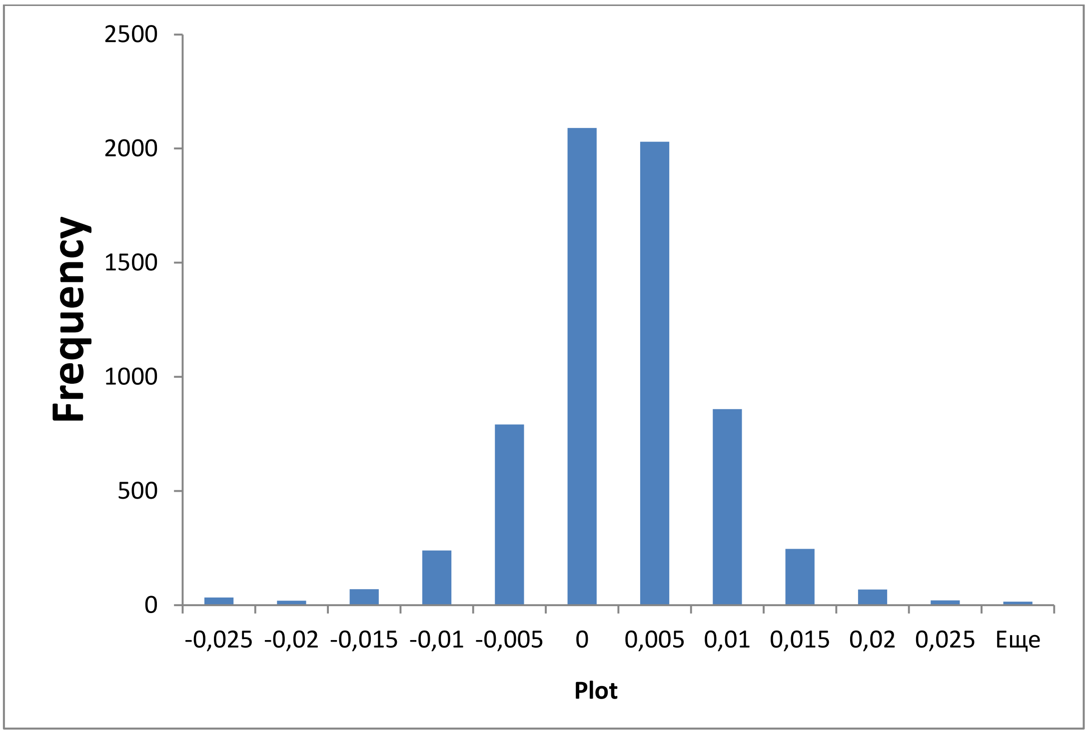


Figure A.4: Frequency distribution of USDCAD, 1994-20189

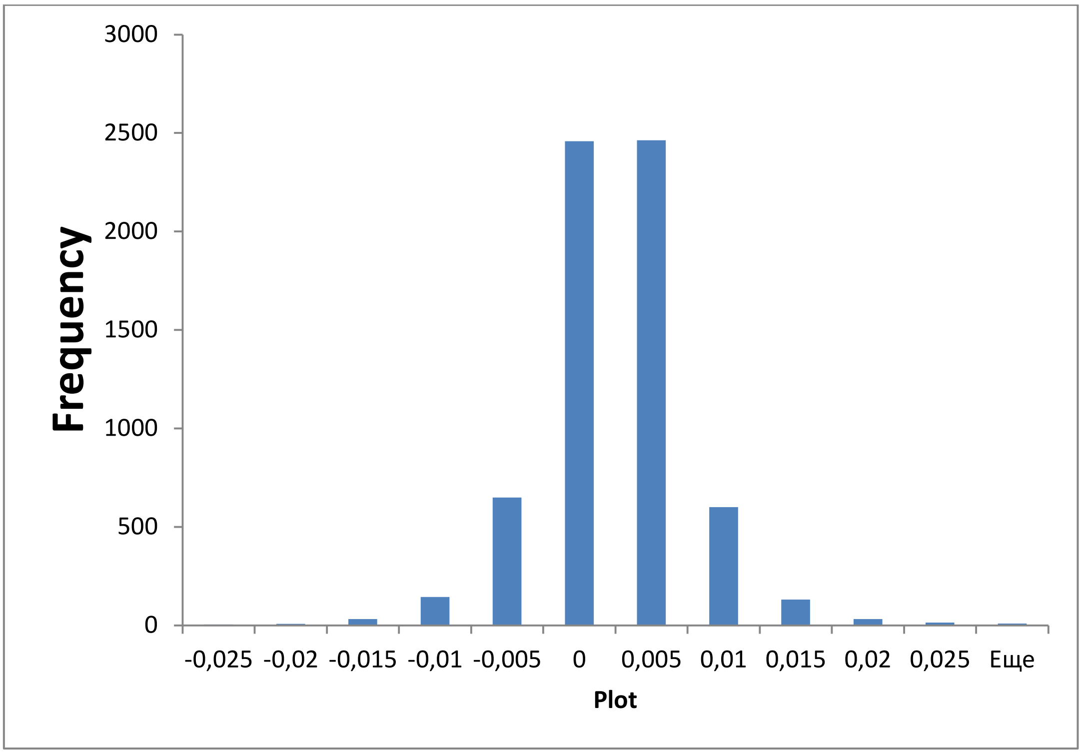


Figure A.5: Frequency distribution of AUDUSD, 1994-2019

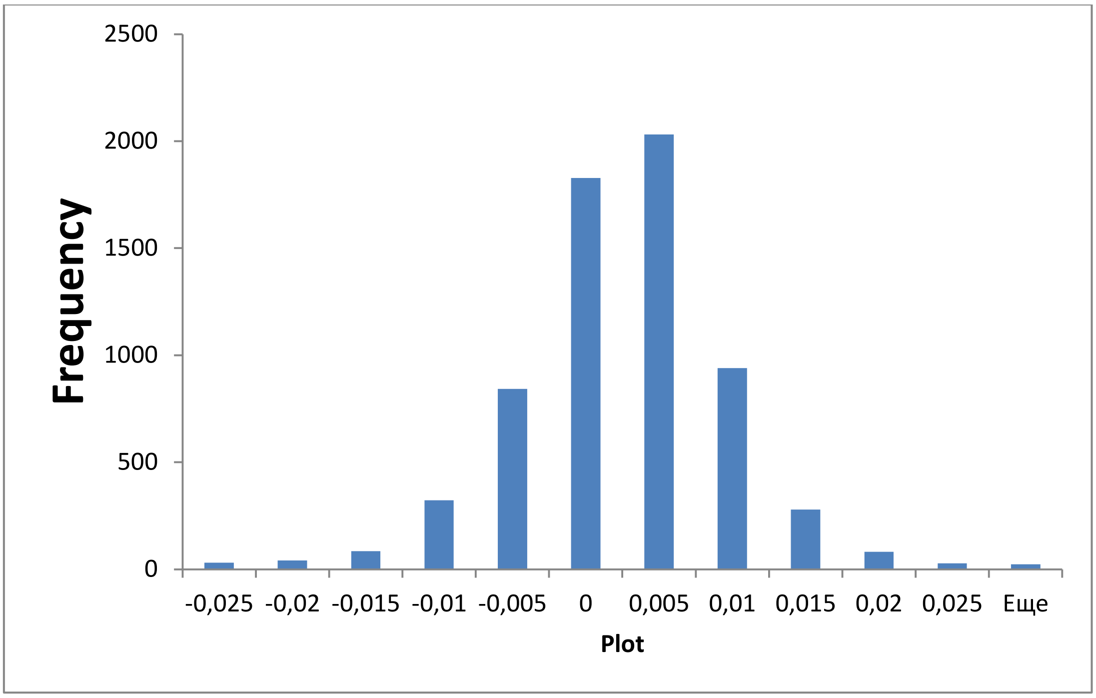


Figure A.6: Frequency distribution of EURJPY, 1994-2019

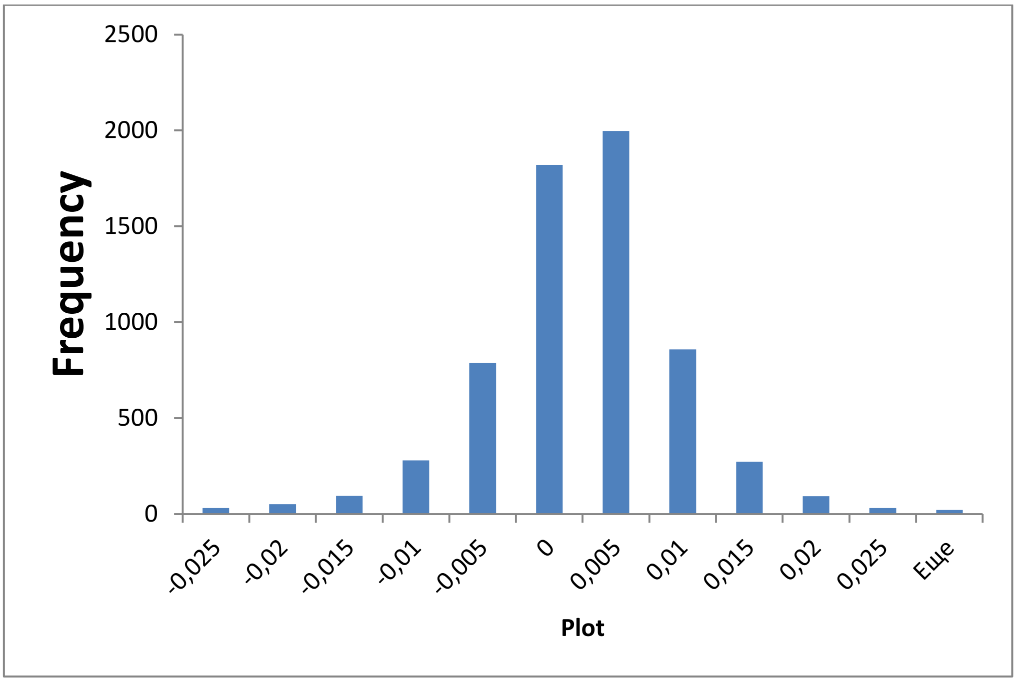
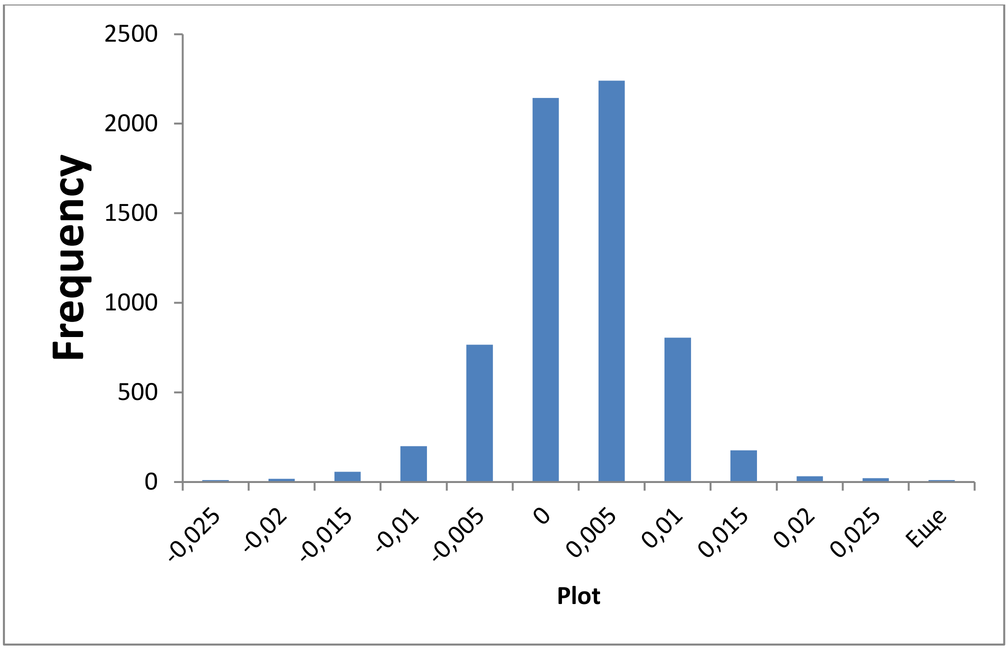


Figure A.7: Frequency distribution of GBPCHF, 1994-2019



These figures present the frequency distribution estimates for FOREX returns (selected assets) over the period 01.01.1994-31.05.2019. The plot size is displayed on the x axis; the number of returns fitting the corresponding plot is displayed on the y axis.

Appendix B

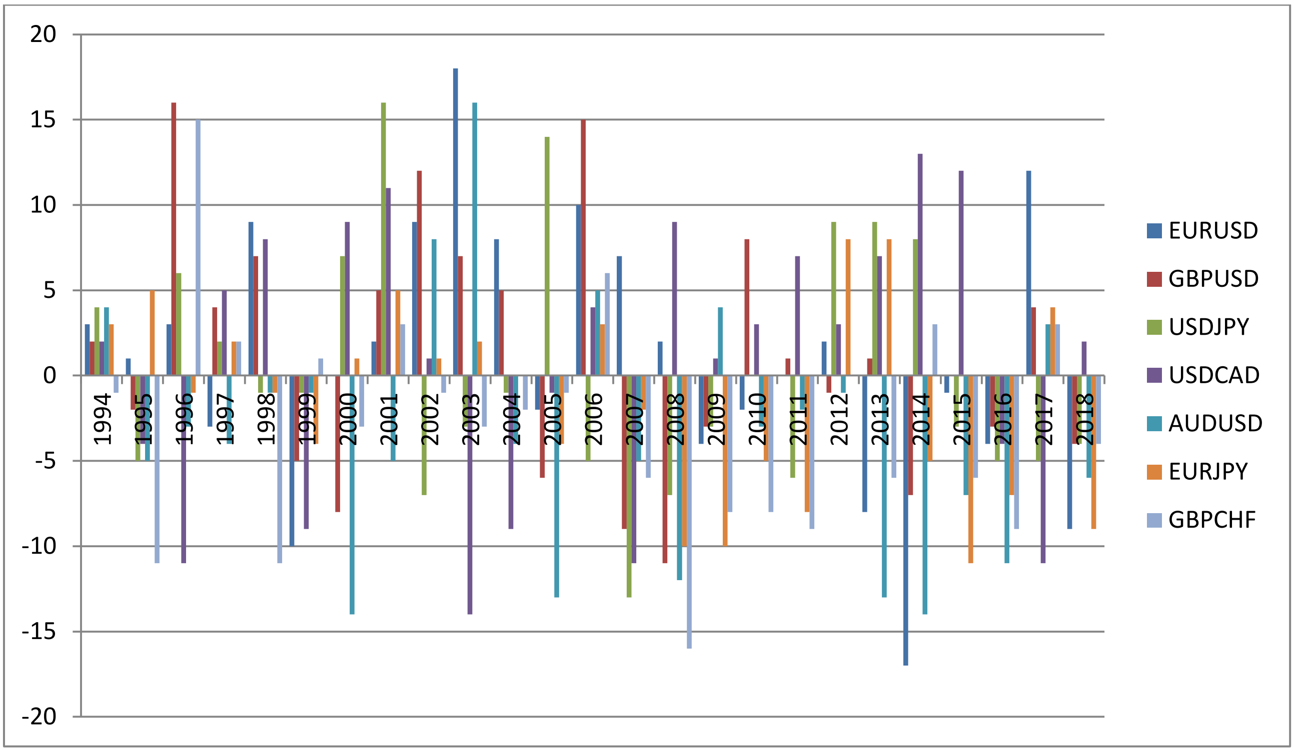
Frequency of abnormal returns

Table B.1: Frequency of abnormal returns over the period 1994-2018, annual

Year	EURUSD	GBPUSD	USDJPY	USDCAD	AUDUSD	EURJPY	GBPCHF	Aver
1994	33	30	28	30	32	31	31	31
1995	37	34	35	40	43	47	35	39
1996	39	40	34	31	39	45	43	39
1997	43	38	36	35	34	36	40	37
1998	39	43	47	42	39	45	39	42
1999	46	39	29	49	33	40	43	40
2000	44	44	39	47	40	21	43	40
2001	38	43	42	45	45	37	49	43
2002	37	42	37	51	42	35	43	41
2003	46	43	39	46	42	42	49	44
2004	48	53	45	47	50	48	54	49
2005	46	42	42	31	47	46	45	43
2006	42	45	37	46	39	43	32	41
2007	47	45	41	47	37	52	52	46
2008	54	57	49	49	46	42	52	50
2009	34	41	37	39	44	38	34	38
2010	44	48	36	41	41	41	42	42
2011	40	45	32	45	44	42	33	40
2012	40	41	47	37	39	44	40	41
2013	32	43	47	43	47	44	46	43
2014	45	39	38	45	40	39	41	41
2015	45	44	35	40	45	39	32	40
2016	42	41	39	40	43	41	41	41
2017	36	36	37	37	35	36	43	37
2018	51	42	34	46	44	39	42	43

This table presents the frequency of abnormal returns estimates for all analyzed instruments over the period 1994-2018. The first column reports the years; the rest shows estimates for overall frequency of abnormal returns per year (both negative and positive) for each currency pair used in this paper.

Figure B.1: Frequency of abnormal returns: dynamic analysis over the period 1994-2018, annual data



This figure presents frequency of abnormal returns estimates in FOREX over the period 1994-2018 for the case of overall frequency of abnormal returns per year (both negative and positive). The frequency of abnormal returns parameter is displayed on the y axis; the year is displayed on the x axis.

Appendix C

Augmented Dickey-Fuller test

Table C.1: Augmented Dickey-Fuller test: EURUSD returns and abnormal returns frequency data

Parameter	returns	delta	negative	positive
Augmented Dickey-Fuller test (Intercept)				
Augmented Dickey-Fuller test statistic	-16.597	-15.377	-17.008	-17.226
Probability	0.0000	0.0000	0.0000	0.0000
Null hypothesis	rejected	rejected	rejected	rejected
Augmented Dickey-Fuller test (Trend and intercept)				
Augmented Dickey-Fuller test statistic	-16.574	-15.460	-17.104	-17.234
Probability	0.0000	0.0000	0.0000	0.0000
Null hypothesis	rejected	rejected	rejected	rejected
Augmented Dickey-Fuller test (Intercept, 1-st difference)				
Augmented Dickey-Fuller test statistic	-7.996	-8.261	-11.697	-8.411
Probability	0.0000	0.0000	0.0000	0.0000
Null hypothesis	rejected	rejected	rejected	rejected

Table C.2: Augmented Dickey-Fuller test: GBRUSD returns and abnormal returns frequency data

Parameter	returns	delta	negative	positive
Augmented Dickey-Fuller test (Intercept)				
Augmented Dickey-Fuller test statistic	-7.444	-8.354	-7.318	-13.866
Probability	0.0000	0.0000	0.0000	0.0000
Null hypothesis	rejected	rejected	rejected	rejected
Augmented Dickey-Fuller test (Trend and intercept)				
Augmented Dickey-Fuller test statistic	-7.539	-8.346	-7.481	-13.875
Probability	0.0000	0.0000	0.0000	0.0000
Null hypothesis	rejected	rejected	rejected	rejected
Augmented Dickey-Fuller test (Intercept, 1-st difference)				
Augmented Dickey-Fuller test statistic	-8.904	-9.296	-8.297	-7.928
Probability	0.0000	0.0000	0.0000	0.0000
Null hypothesis	rejected	rejected	rejected	rejected

Table C.3: Augmented Dickey-Fuller test: EURJPY returns and abnormal returns frequency data

Parameter	returns	delta	Negative	Positive
Augmented Dickey-Fuller test (Intercept)				
Augmented Dickey-Fuller test statistic	-17.267	-16.921	-19.612	-17.412
Probability	0.0000	0.0000	0.0000	0.0000
Null hypothesis	rejected	rejected	rejected	rejected
Augmented Dickey-Fuller test (Trend and intercept)				
Augmented Dickey-Fuller test statistic	-17.241	-17.031	-19.661	-17.446
Probability	0.0000	0.0000	0.0000	0.0000

Null hypothesis	rejected	rejected	rejected	rejected
Augmented Dickey-Fuller test (Intercept, 1-st difference)				
Augmented Dickey-Fuller test statistic	-8.705	-9.705	-9.488	-9.016
Probability	0.0000	0.0000	0.0000	0.0000
Null hypothesis	rejected	rejected	rejected	rejected

Table C.4: Augmented Dickey-Fuller test: USDJPY returns and abnormal returns frequency data

Parameter	returns	delta	Negative	Positive
Augmented Dickey-Fuller test (Intercept)				
Augmented Dickey-Fuller test statistic	-8.833	-15.777	-19.614	-8.697
Probability	0.0000	0.0000	0.0000	0.0000
Null hypothesis	rejected	rejected	rejected	rejected
Augmented Dickey-Fuller test (Trend and intercept)				
Augmented Dickey-Fuller test statistic	-8.816	-15.791	-19.656	-8.696
Probability	0.0000	0.0000	0.0000	0.0000
Null hypothesis	rejected	rejected	rejected	rejected
Augmented Dickey-Fuller test (Intercept, 1-st difference)				
Augmented Dickey-Fuller test statistic	-7.006	-10.180	-10.182	-9.821
Probability	0.0000	0.0000	0.0000	0.0000
Null hypothesis	rejected	rejected	rejected	rejected

Table C.5: Augmented Dickey-Fuller test: GBRCHF returns and abnormal returns frequency data

Parameter	returns	delta	Negative	Positive
Augmented Dickey-Fuller test (Intercept)				
Augmented Dickey-Fuller test statistic	-19.056	-17.746	-18.303	-18.060
Probability	0.0000	0.0000	0.0000	0.0000
Null hypothesis	rejected	rejected	rejected	rejected
Augmented Dickey-Fuller test (Trend and intercept)				
Augmented Dickey-Fuller test statistic	-19.098	-17.795	-18.295	-18.100
Probability	0.0000	0.0000	0.0000	0.0000
Null hypothesis	rejected	rejected	rejected	rejected
Augmented Dickey-Fuller test (Intercept, 1-st difference)				
Augmented Dickey-Fuller test statistic	-9.991	-10.070	-8.841	-8.800
Probability	0.0000	0.0000	0.0000	0.0000
Null hypothesis	rejected	rejected	rejected	rejected

Table C.6: Augmented Dickey-Fuller test: AUDUSD returns and abnormal returns frequency data

Parameter	returns	delta	Negative	Positive
Augmented Dickey-Fuller test (Intercept)				
Augmented Dickey-Fuller test statistic	-16.166	-16.478	-17.065	-14.451
Probability	0.0000	0.0000	0.0000	0.0000
Null hypothesis	rejected	rejected	rejected	rejected

Augmented Dickey-Fuller test (Trend and intercept)				
Augmented Dickey-Fuller test statistic	-16.146	-16.553	-17.167	-14.441
Probability	0.0000	0.0000	0.0000	0.0000
Null hypothesis	rejected	rejected	rejected	rejected
Augmented Dickey-Fuller test (Intercept, 1-st difference)				
Augmented Dickey-Fuller test statistic	-8.133	-9.462	-8.049	-9.528
Probability	0.0000	0.0000	0.0000	0.0000
Null hypothesis	rejected	rejected	rejected	rejected

Table C.7: Augmented Dickey-Fuller test: USDCAD returns and abnormal returns frequency data

Parameter	**returns**	**delta**	**Negative**	**Positive**
Augmented Dickey-Fuller test (Intercept)				
Augmented Dickey-Fuller test statistic	-7.789	-18.762	-8.534	-17.537
Probability	0.0000	0.0000	0.0000	0.0000
Null hypothesis	rejected	rejected	rejected	rejected
Augmented Dickey-Fuller test (Trend and intercept)				
Augmented Dickey-Fuller test statistic	-7.815	-18.796	-8.540	-17.621
Probability	0.0000	0.0000	0.0000	0.0000
Null hypothesis	rejected	rejected	rejected	rejected
Augmented Dickey-Fuller test (Intercept, 1-st difference)				
Augmented Dickey-Fuller test statistic	-10.090	-7.367	-8.537	-9.266
Probability	0.0000	0.0000	0.0000	0.0000
Null hypothesis	rejected	rejected	rejected	rejected

These tables present the results of the Augmented Dickey-Fuller test. The first specifies the parameter of the Augmented Dickey-Fuller test being considered, the second column shows the results for returns (“returns”); the third column for delta frequency data (“delta”); the fourth column shows parameter estimates for negative abnormal returns (“Negative”) and the fifth column for positive abnormal returns (“Positive”). The Lag Length was chosen on the basis of the Akaike information criterion. The results are significant at the 5% level.

Appendix D

Cross-correlation analysis

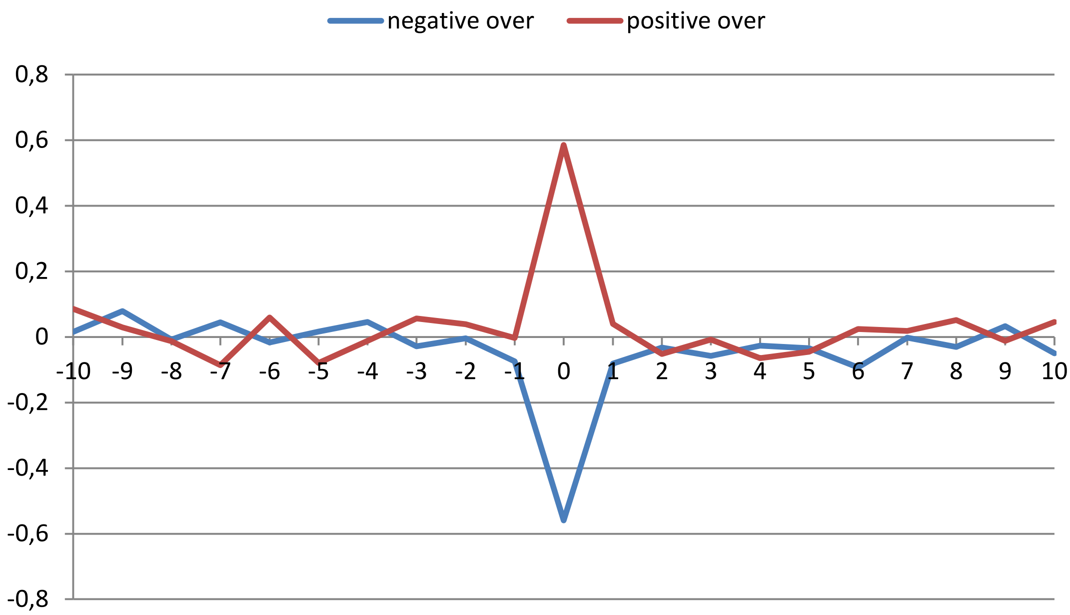


Figure D.1: Cross-correlation between EURUSD returns and frequency of abnormal returns over the whole sample period for different leads and lags

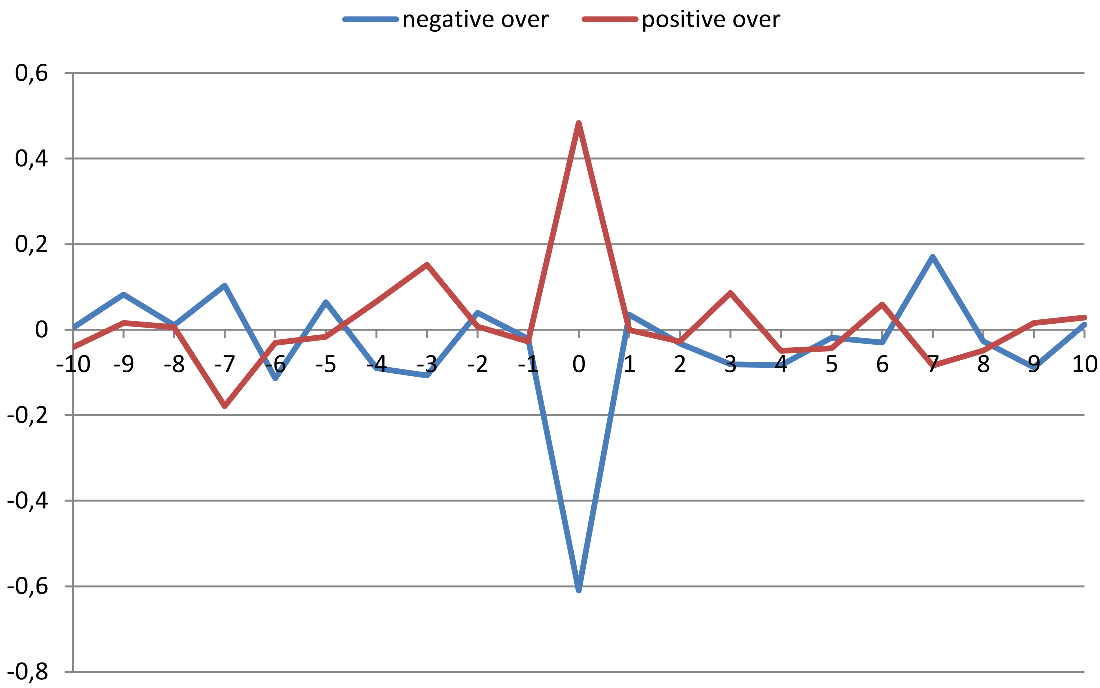


Figure D.2: Cross-correlation between GBPUSD returns and frequency of abnormal returns over the whole sample period for different leads and lags

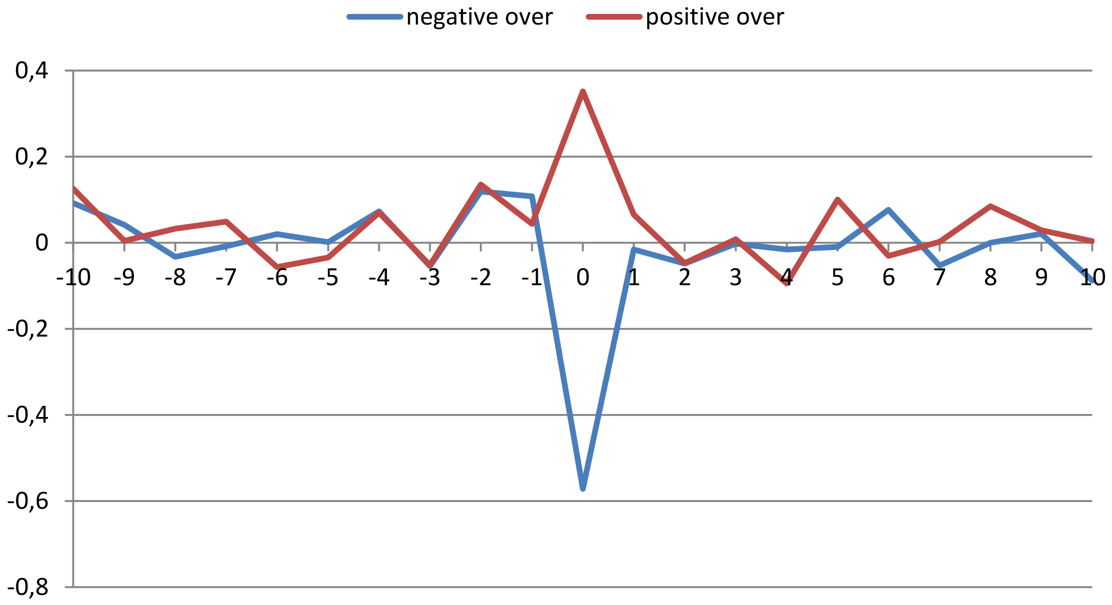


Figure D.3: Cross-correlation between EURJPY returns and frequency of abnormal returns over the whole sample period for different leads and lags

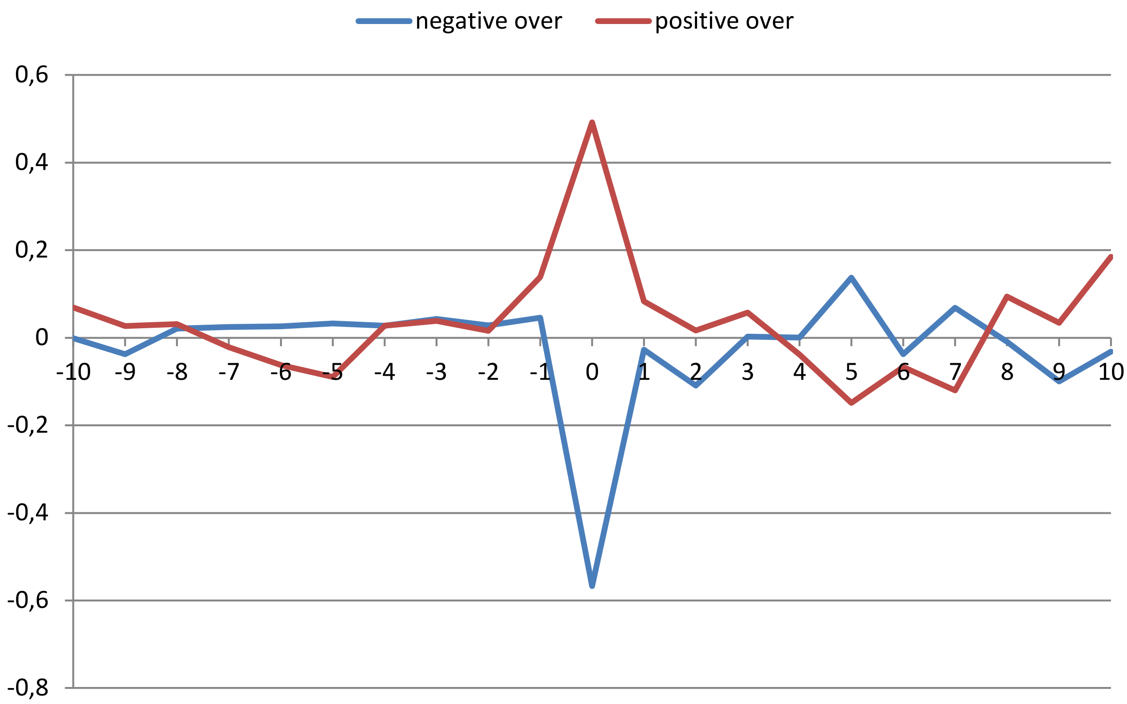


Figure D.4: Cross-correlation between USDJPY returns and frequency of abnormal returns over the whole sample period for different leads and lags

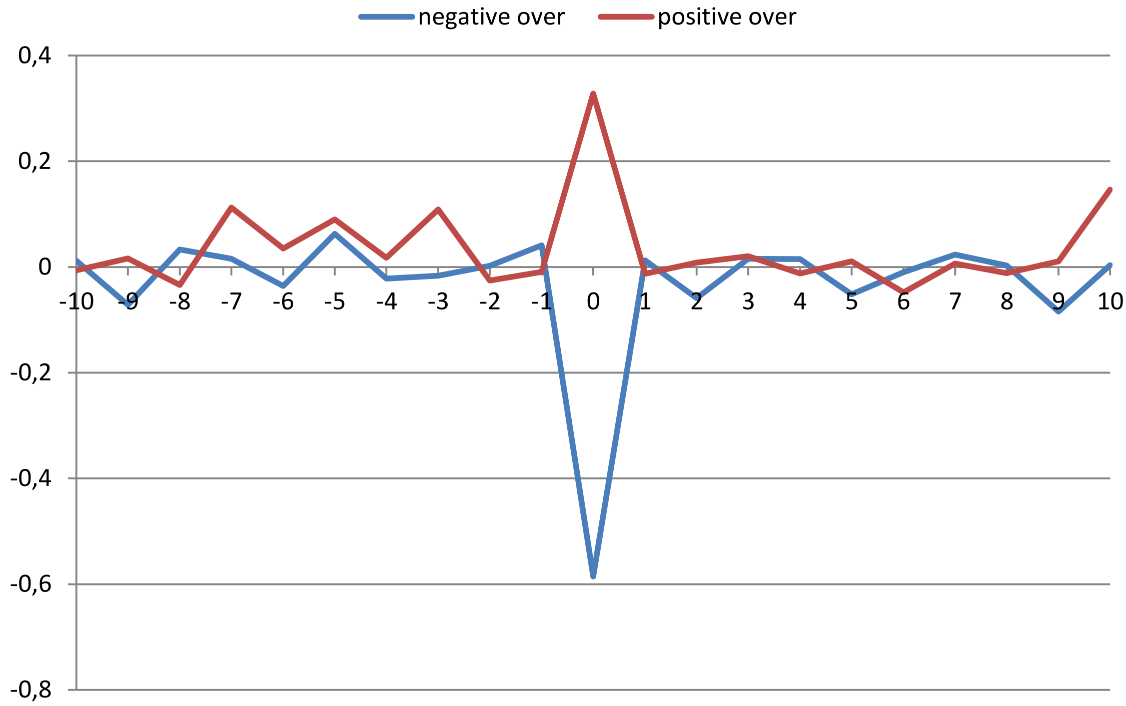


Figure D.5: Cross-correlation between GBPCHF returns and frequency of abnormal returns over the whole sample period for different leads and lags

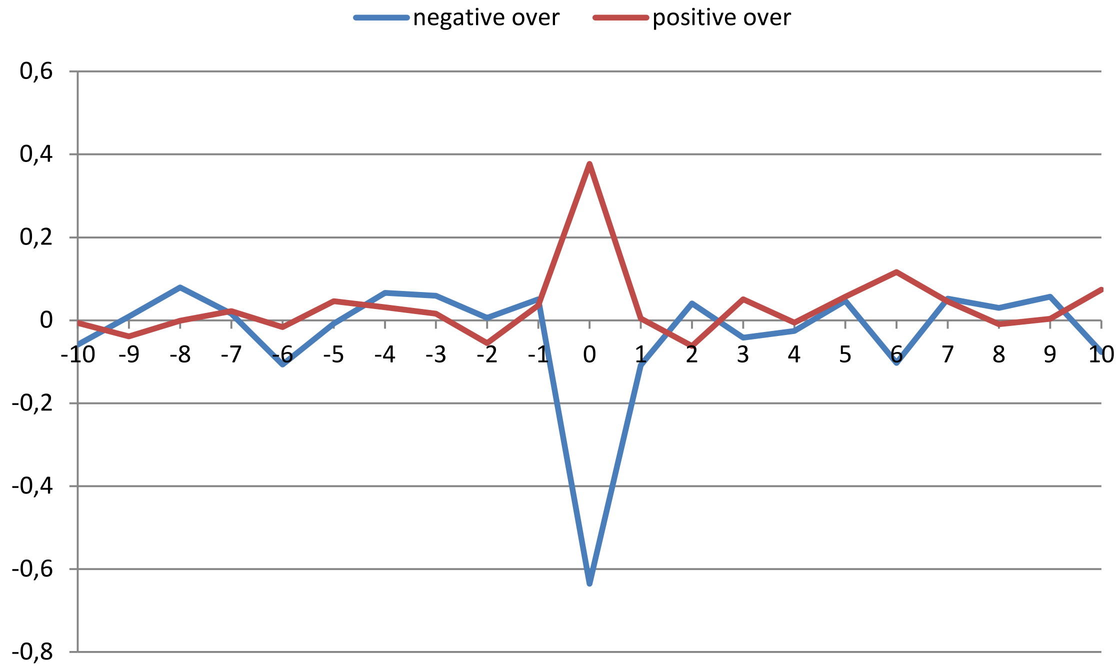


Figure D.6: Cross-correlation between AUDUSD returns and frequency of abnormal returns over the whole sample period for different leads and lags

Figure D.7: Cross-correlation between USDCAD returns and frequency of abnormal returns over the whole sample period for different leads and lags

These figures display the correlation coefficients between returns and the frequency of negative abnormal returns ("negative over") as well as the frequency of positive abnormal returns ("positive over") over the whole sample period with lags in the interval [-10…+10].

Appendix E

Regression analysis

Table E.1: Regression analysis results: the case of EURUSD

Parameter	Frequency delta abnormal returns	Frequency of negative and positive abnormal returns as separate variables
a_0	-0.0005 (0.632)	-0.0035 (0.147)
Slope for the abnormal returns ($case\ of\ delta\ abnormal\ returns$)	0.0109 (0.000)	-
Slope for the abnormal returns ($case\ of\ negative\ abnormal\ returns$)	-	-0.0101 (0.000)
Slope for the abnormal returns ($case\ of\ positive\ abnormal\ returns$)	-	0.0119 (0.000)
F-test	400.533 (0.000)	201.828 (0.000)
Multiple R	0.7577	0.759

* P-values are in parentheses

Table E.2: Regression analysis results: the case of GBRUSD

Parameter	Frequency delta abnormal returns	Frequency of negative and positive abnormal returns as separate variables
a_0	-0.0011(0.221)	0.0029(0.154)
Slope for the abnormal returns ($case\ of\ delta\ abnormal\ returns$)	0.0091(0.000)	-
Slope for the abnormal returns ($case\ of\ negative\ abnormal\ returns$)	-	-0.0102(0.000)
Slope for the abnormal returns ($case\ of\ positive\ abnormal\ returns$)	-	0.0079(0.000)
F-test	363.993(0.000)	186.8131(0.000)
Multiple R	0.7420	0.7469

* P-values are in parentheses

Table E.3: Regression analysis results: the case of EURJPY

Parameter	Frequency delta abnormal returns	Frequency of negative and positive abnormal

		returns as separate variables
a_0	0.0022(0.113)	0.0069(0.0122)
Slope for the abnormal returns ($case\ of\ delta\ abnormal\ returns$)	0.0133(0.000)	-
Slope for the abnormal returns ($case\ of\ negative\ abnormal\ returns$)	-	-0.0144(0.000)
Slope for the abnormal returns ($case\ of\ positive\ abnormal\ returns$)	-	0.0117(0.000)
F-test	293.817(0.000)	150.316(0.000)
Multiple R	0.7051	0.7098

* P-values are in parentheses

Table E.4: Regression analysis results: the case of USDJPY

Parameter	Frequency delta abnormal returns	Frequency of negative and positive abnormal returns as separate variables
a_0	0.0002(0.818)	0.0025(0.3187)
Slope for the abnormal returns ($case\ of\ delta\ abnormal\ returns$)	0.0116(0.000)	-
Slope for the abnormal returns ($case\ of\ negative\ abnormal\ returns$)	-	-0.0123(0.000)
Slope for the abnormal returns ($case\ of\ positive\ abnormal\ returns$)	-	0.0109(0.000)
F-test	336.758(0.000)	168.9291(0.000)
Multiple R	0.7289	0.7300

* P-values are in parentheses

Table E.5: Regression analysis results: the case of GBRCHF

Parameter	Frequency delta abnormal returns	Frequency of negative and positive abnormal returns as separate variables
a_0	0.0009(0.437)	0.0072(0.005)
Slope for the abnormal returns ($case\ of\ delta\ abnormal\ returns$)	0.0100(0.000)	-
Slope for the abnormal returns ($case\ of\ negative\ abnormal\ returns$)	-	-0.0115(0.000)
Slope for the abnormal returns ($case\ of\ positive\ abnormal\ returns$)	-	0.0078(0.000)
F-test	235.161(0.000)	123.9794(0.000)
Multiple R	0.6647	0.6751

* P-values are in parentheses

Table E.6: Regression analysis results: the case of AUDUSD

Parameter	Frequency delta abnormal returns	Frequency of negative and positive abnormal returns as separate variables
a_0	0.0040(0.004)	0.013(0.000)
Slope for the abnormal returns ($case\ of\ delta\ abnormal\ returns$)	0.0124(0.000)	-
Slope for the abnormal returns ($case\ of\ negative\ abnornal\ returns$)	-	-0.0146(0.000)
Slope for the abnormal returns ($case\ of\ positive\ abnornal\ returns$)	-	0.0093(0.000)
F-test	281.889(0.000)	150.6391(0.000)
Multiple R	0.6978	0.7102

* P-values are in parentheses

Table E.7: Regression analysis results: the case of USDCAD

Parameter	Frequency delta abnormal returns	Frequency of negative and positive abnormal returns as separate variables
a_0	-0.0003(0.740)	-0.0050(0.022)
Slope for the abnormal returns ($case\ of\ delta\ abnormal\ returns$)	0.0091(0.000)	-
Slope for the abnormal returns ($case\ of\ negative\ abnornal\ returns$)	-	-0.0076(0.000)
Slope for the abnormal returns ($case\ of\ positive\ abnornal\ returns$)	-	0.0104(0.000)
F-test	322.329(0.000)	166.5997(0.000)
Multiple R	0.7214	0.7277

* P-values are in parentheses

These tables present the coefficient estimates and p-values (in parentheses) from the regression models. The second column reports the parameter estimates for delta frequency, the third for the frequency of both positive and negative abnormal returns as separate variables.

Appendix F

Logit and Probit regression analysis

Table F.1: Logit and Probit regression analysis results: the case of EURUSD

Parameter	Logit		Probit	
a_0	-0.0031 (0.982)	-0.1141 (0.723)	-0.0044 (0.958)	-0.0816 (0.674)
Slope for the abnormal returns ($case\ of\ frequency\ delta$)	0.9365 (0.000)	-	0.5501 (0.000)	-
Slope for the abnormal returns ($case\ of\ negative\ abnornal\ returns$)	-	-0.9029 (0.000)	-	-0.5276 (0.000)
Slope for the abnormal returns ($case\ of\ positive\ abnornal\ returns$)	-	0.9718 (0.000)	-	0.5747 (0.000)
McFadden R-squared	0.2994	0.2998	0.3003	0.3007
Akaike AIC	294.185	296.037	293.832	295.636
The number of "correctly predicted" cases, %	73.9	73.9	73.9	73.9
LR statistic	124.046 (0.000)	124.194 (0.000)	124.399 (0.000)	124.594 (0.000)

Table F.2: Logit and Probit regression analysis results: the case of GBRUSD

Parameter	Logit		Probit	
a_0	-0.0847 (0.4670)	-0.1408 (0.6473)	-0.0528 (0.4679)	-0.0814 (0.6589)
Slope for the abnormal returns ($case\ of\ frequency\ delta$)	0.1115 (0.0684)	-	0.0699 (0.0671)	-
Slope for the abnormal returns ($case\ of\ negative\ abnornal\ returns$)	-	-1.1166 (0.0000)	-	-0.6530 (0.0000)
Slope for the abnormal returns ($case\ of\ positive\ abnornal\ returns$)	-	1.0821 (0.0000)	-	0.6320 (0.0000)
McFadden R-squared	0.0081	0.3358	0.0081	0.3375
Akaike AIC	414.715	281.038	414.706	280.338
The number of "correctly predicted" cases, %	53.5	76.3	53.5	76.3
LR statistic	3.382 (0.0659)	139.058 (0.0000)	3.390 (0.0656)	139.759 (0.0000)

Table F.3: Logit and Probit regression analysis results: the case of EURJPY

Parameter	Logit		Probit	
a_0	0.4118 (0.0044)	0.5772 (0.0270)	0.2437 (0.0039)	0.3622 (0.0197)
Slope for the abnormal returns ($case\ of\ frequency\ delta$)	0.9569 (0.0000)	-	0.5585 (0.0000)	-
Slope for the abnormal returns ($case\ of\ negative\ abnornal\ returns$)	-	-1.0008 (0.0000)	-	-0.5910 (0.0000)
Slope for the abnormal returns ($case\ of\ positive\ abnornal\ returns$)	-	0.8914 (0.0000)	-	0.5151 (0.0000)
McFadden R-squared	0.2741	0.2755	0.2740	0.2760

Akaike AIC	301.882	303.296	301.940	303.107
The number of "correctly predicted" cases, %	73.2	73.2	73.2	73.2
LR statistic	112.513 (0.0000)	113.099 (0.0000)	112.455 (0.0000)	113.288 (0.0000)

Table F.4: Logit and Probit regression analysis results: the case of USDJPY

Parameter	Logit		Probit	
a_0	0.0446 (0.7612)	-0.2121 (0.4591)	0.0258 (0.7639)	-0.1018 (0.5528)
Slope for the abnormal returns ($case\ of\ frequency\ delta$)	1.0724 (0.0000)	-	0.6154 (0.0000)	-
Slope for the abnormal returns ($case\ of\ negative\ abnornal\ returns$)	-	-0.9977 (0.0000)	-	-0.5765 (0.0000)
Slope for the abnormal returns ($case\ of\ positive\ abnornal\ returns$)	-	1.1823 (0.0000)	-	0.6659 (0.0000)
McFadden R-squared	0.3241	0.3267	0.3224	0.0114
Akaike AIC	184.105	285.010	284.806	286.065
The number of "correctly predicted" cases, %	73.2	76.6	73.2	76.6
LR statistic	134.313 (0.0000)	135.408 (0.0000)	133.612 (0.0000)	134.353 (0.0000)

Table F.5: Logit and Probit regression analysis results: the case of GBRCHF

Parameter	Logit		Probit	
a_0	0.0686 (0.6317)	0.6066 (0.0408)	0.0358 (0.6697)	0.3606 (0.0422)
Slope for the abnormal returns ($case\ of\ frequency\ delta$)	0.9568 (0.0000)	-	0.5608 (0.0000)	-
Slope for the abnormal returns ($case\ of\ negative\ abnornal\ returns$)	-	-1.1082 (0.0000)	-	-0.6503 (0.0000)
Slope for the abnormal returns ($case\ of\ positive\ abnornal\ returns$)	-	0.7748 (0.0000)	-	0.4512 (0.0000)
McFadden R-squared	0.2801	0.2909	0.2802	0.0001
Akaike AIC	301.825	299.382	301.798	299.4012
The number of "correctly predicted" cases, %	75.3	75.3	75.3	75.3
LR statistic	115.924 (0.0000)	120.367 (0.0000)	115.951 (0.0000)	120.348 (0.0000)

Table F.6: Logit and Probit regression analysis results: the case of AUDUSD

Parameter	Logit		Probit	
a_0	0.3401 (0.0265)	0.3234 (0.2964)	0.2009 (0.0238)	0.2045 (0.2666)
Slope for the abnormal returns ($case\ of\ Frequency\ delta$)	1.0510 (0.0000)	-	0.6198 (0.0000)	-
Slope for the abnormal returns ($case\ of\ negative\ abnornal\ returns$)	-	-1.0467 (0.0000)	-	-0.6207 (0.0000)
Slope for the abnormal returns	-	1.0577	-	0.6184

$(case\ of\ positive\ abnornal\ returns)$		(0.0000)		(0.0000)
McFadden R-squared	0.3310	0.3310	0.3330	0.3330
Akaike AIC	281.223	283.220	280.394	282.393
The number of “correctly predicted” cases, %	77.6	77.6	77.6	77.6
LR statistic	137.194 (0.0000)	137.198 (0.0000)	138.024 (0.0000)	138.025 (0.0000)

Table F.7: Logit and Probit regression analysis results: the case of USDCAD

Parameter	Logit		Probit	
a_0	-0.0701 (0.6359)	-0.3481 (0.2885)	-0.0326 (0.7041)	-0.1969 (0.3044)
Slope for the abnormal returns $(case\ of\ frequency\ delta)$	1.0390 (0.0000)	-	0.6073 (0.0000)	-
Slope for the abnormal returns $(case\ of\ negative\ abnornal\ returns)$	-	-0.9524 (0.0000)	-	-0.5576 (0.0000)
Slope for the abnormal returns $(case\ of\ positive\ abnornal\ returns)$	-	1.1250 (0.0000)	-	0.6570 (0.0000)
McFadden R-squared	0.3253	0.3275	0.3255	0.3277
Akaike AIC	283.629	284.719	283.571	284.647
The number of “correctly predicted” cases, %	77.6	77.9	77.6	77.9
LR statistic	134.869 (0.0000)	135.779 (0.0000)	134.927 (0.0000)	135.851 (0.0000)

These tables present results for monthly price closes regressed against frequency of negative and positive abnormal returns as well as delta frequency. Coefficient estimates and p-values (in parentheses) from regression models are provided in these tables. The first column reports the model parameters, the second and third the estimates from the Logit models, and the fourth and fifth those from the Probit models.

Appendix G

Granger Causality Tests

Table G.1: Granger Causality Tests between returns and frequency of negative and positive abnormal returns and delta frequency

X	Y (returns)			Y (returns)			Y (returns)		
	Chi-sq	Probability	Null Hypothesis	Chi-sq	Probability	Null Hypothesis	Chi-sq	Probability	Null Hypothesis
Negative	1.63	0.20	not rejected	0.59	0.44	not rejected	0.06	0.80	not rejected
Positive	0.20	0.65	not rejected	0.00	0.99	not rejected	1.92	0.17	not rejected
Delta	2.18	0.14	not rejected	0.38	0.54	not rejected	1.97	0.16	not rejected
Y	X (returns)			X (returns)			X (returns)		
Negative	2.11	0.15	not rejected	2.48	0.11	not rejected	0.45	0.50	not rejected
Positive	0.00	0.98	not rejected	0.00	0.94	not rejected	6.00	0.01	rejected
Delta	0.75	0.38	not rejected	0.22	0.64	not rejected	0.00	0.99	not rejected
	USDCAD			AUDUSD			EURJPY		

X	Y (returns)			Y (returns)			Y (returns)		
	Chi-sq	Probability	Null Hypothesis	Chi-sq	Probability	Null Hypothesis	Chi-sq	Probability	Null Hypothesis
Negative	0.62	0.43	not rejected	2.35	0.12	not rejected	0.07	0.79	not rejected
Positive	0.24	0.62	not rejected	0.09	0.76	not rejected	1.61	0.20	not rejected
Delta	0.07	0.78	not rejected	0.94	0.33	not rejected	1.98	0.16	not rejected
Y	X (returns)			X (returns)			X (returns)		
Negative	0.21	0.65	not rejected	1.55	0.21	not rejected	0.40	0.52	not rejected
Positive	0.86	0.35	not rejected	1.65	0.20	not rejected	0.79	0.37	not rejected
Delta	0.00	0.94	not rejected	1.01	0.32	not rejected	2.36	0.12	not rejected

	GBPCHF					
Parameter	Y (returns)			X (returns)		
	Chi-sq	Probability	Null Hypothesis	Chi-sq	Probability	Null Hypothesis
Negative	0.93	0.33	not rejected	0.00	0.99	not rejected
Positive	0.12	0.72	not rejected	0.00	0.97	not rejected
Delta	1.19	0.27	not rejected	0.14	0.70	not rejected

Appendix H

Distribution of returns: actual vs estimated (from the regression model and the actual data)

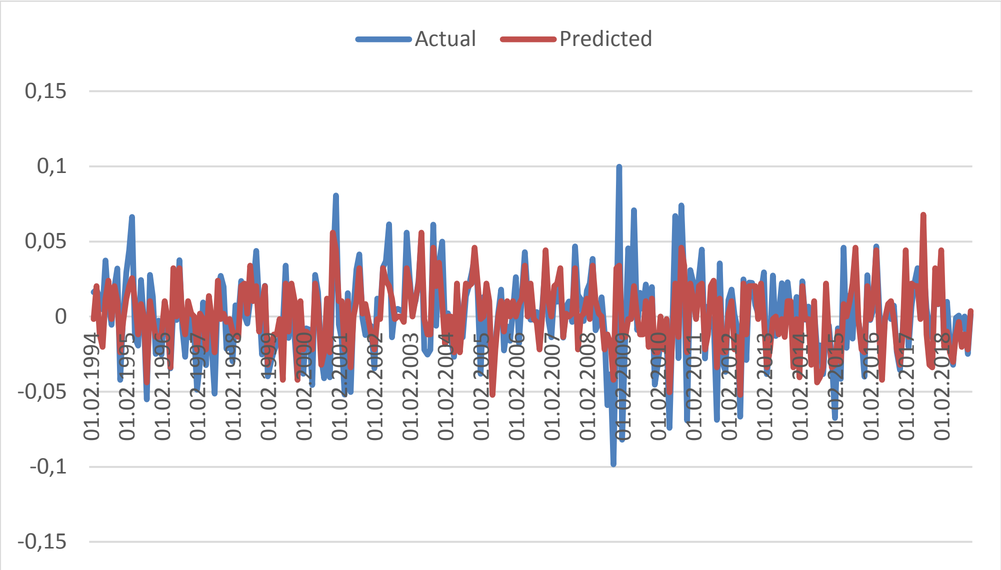


Figure H.1: Distribution of returns: actual vs estimated (from the regression model and the actual data): case of EURUSD

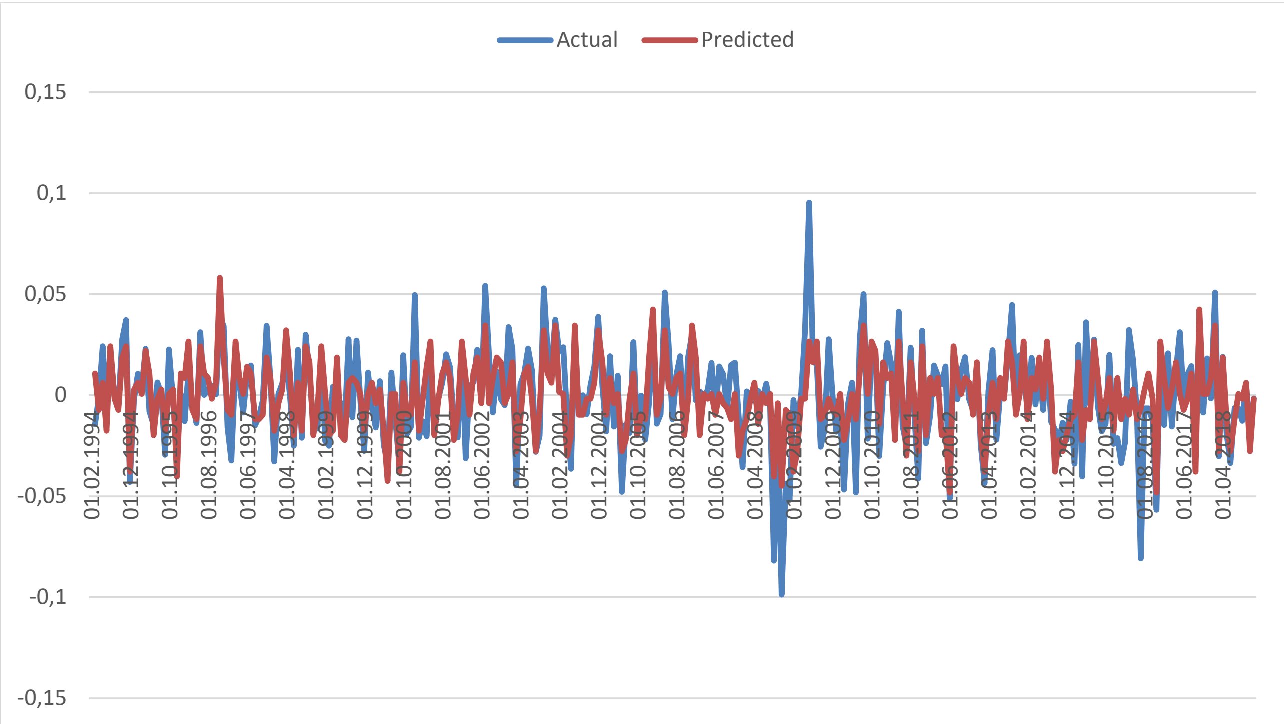


Figure H.2: Distribution of returns: actual vs estimated (from the regression model and the actual data): case of GBPUSD

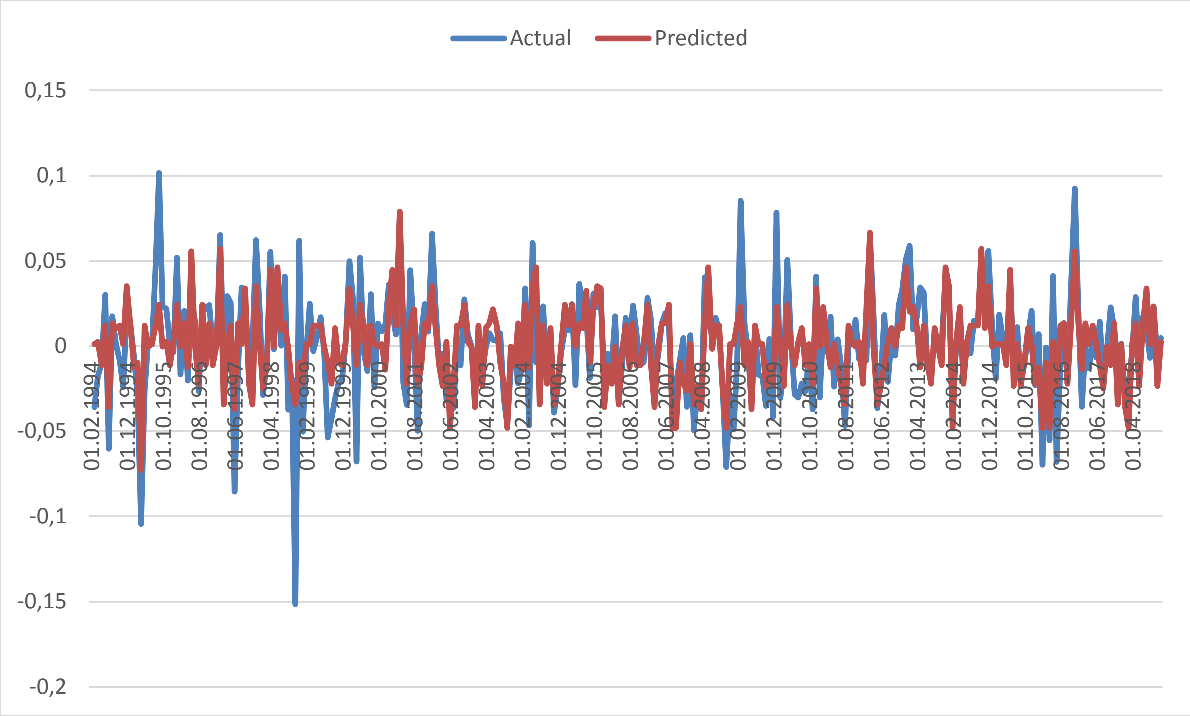


Figure H.3: Distribution of returns: actual vs estimated (from the regression model and the actual data): case of USDJPY

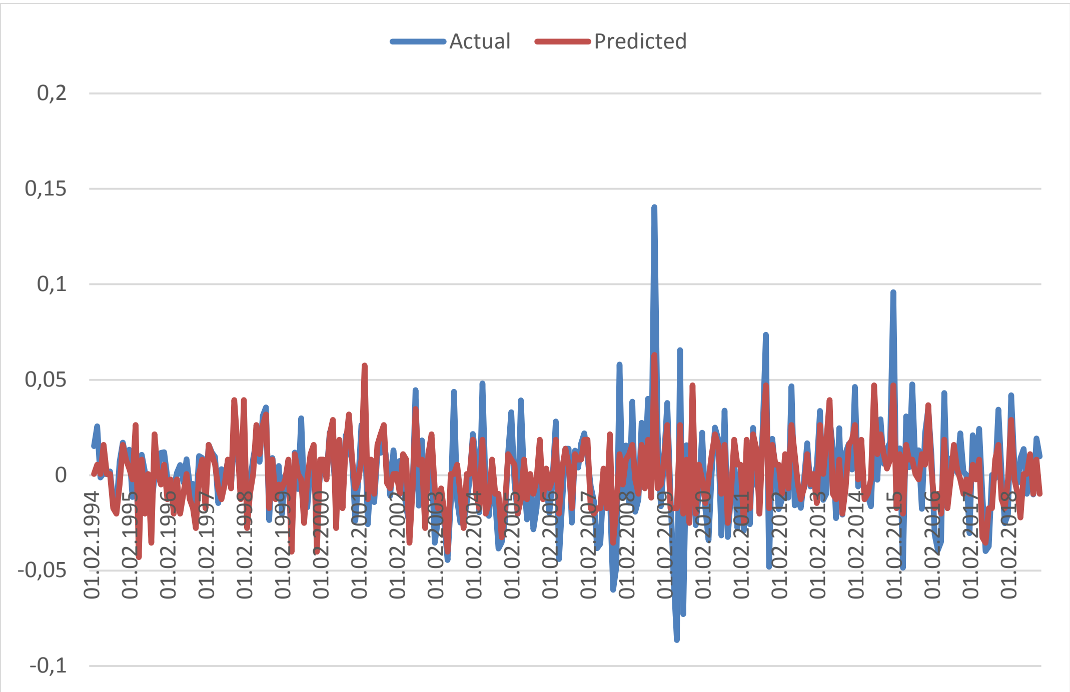


Figure H.4: Distribution of returns: actual vs estimated (from the regression model and the actual data): case of USDCAD

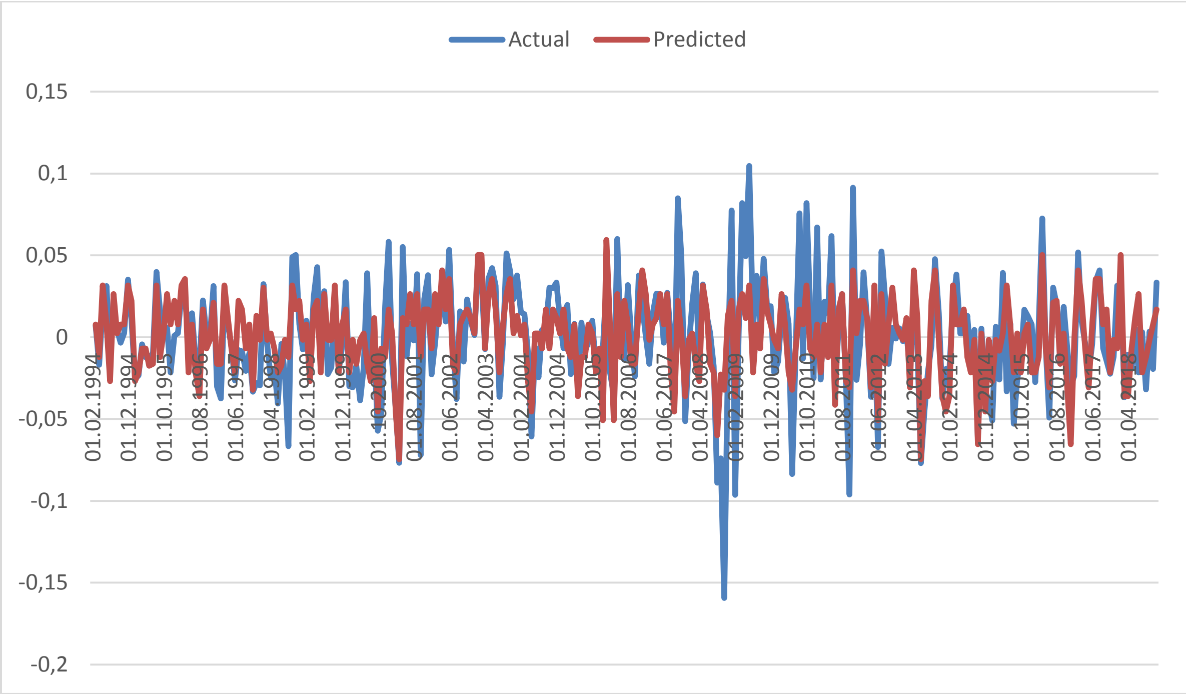


Figure H.5: Distribution of returns: actual vs estimated (from the regression model and the actual data): case of AUDUSD

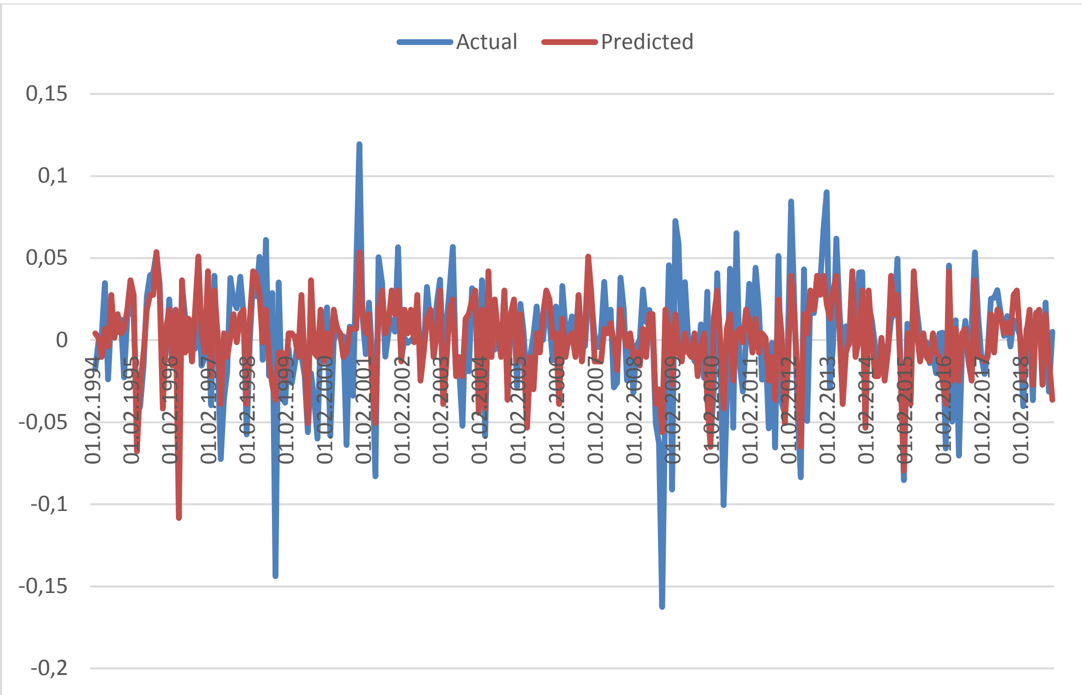


Figure H.6: Distribution of returns: actual vs estimated (from the regression model and the actual data): case of EURJPY

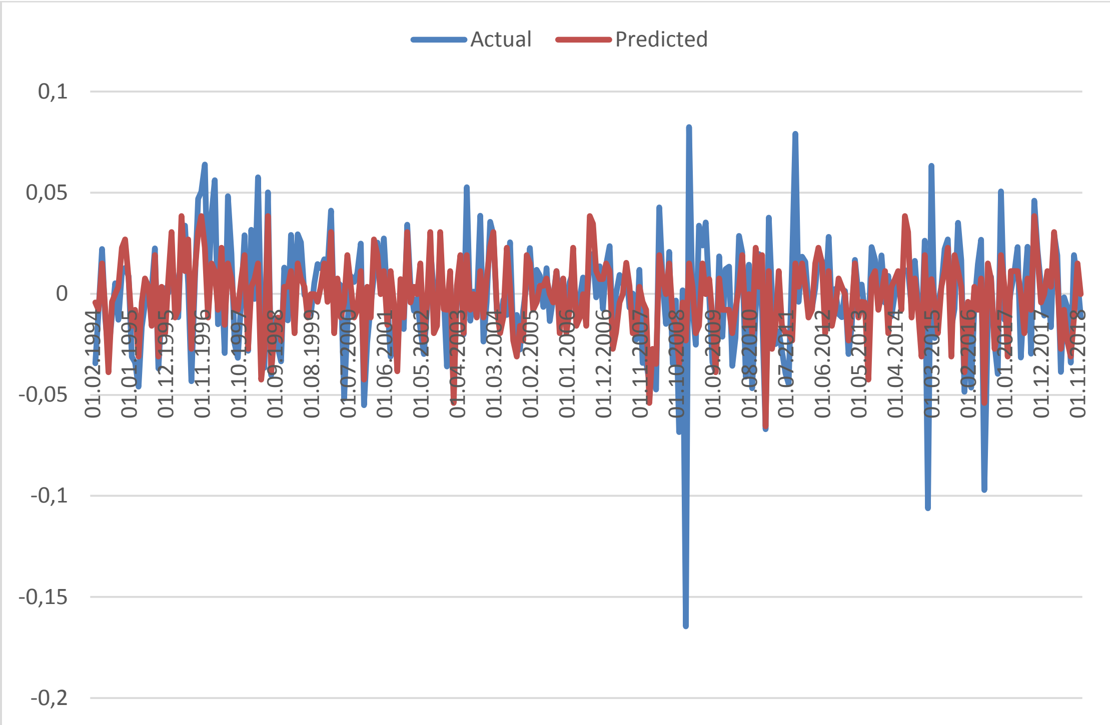


Figure H.7: Distribution of returns: actual vs estimated (from the regression model and the actual data): case of GBPCHF