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How Much Do the Central Bank Announcements Matter on Financial Market? Application of the Rule-Based Trading System Approach

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ABSTRACT:

This paper proposes a rule-based trading system to investigate how much the central bank's announcements matter on a financial market. We design a novel investment strategy and we simulate trades in order to quantify their profitability in the out–of–sample period using the data from a broad financial market in Poland spanning across 3 segments: stock market, foreign exchange market and bonds market.

Our results show that the individual transactions delivered profits in 72.7% cases. The overall profitability across all events and all trading horizons was positive in as many as 63.6% cases.

Although the financial market in Poland was only moderately sensitive to the NBP central bank's communication, the identified types of the monetary policy announcements are economically significant and very useful for the investors, who can trade based on them and exploit them directly in the design of the rule-based trading strategies.

Keywords: Rule-based trading system; Central bank; Monetary policy; Stock market; Foreign exchange market; Bonds market.

1. Introduction

Trading systems constructed on financial markets, which are designed for prediction of financial instruments prices and investing in financial assets, can be divided according to the following two broad principles. The first group concerns entirely rule-based systems, while the second approach is more flexible and also more subjective, where only some general guidelines are used but there are typically no fixed rules adopted.

In this paper, we propose a rule-based trading system related to the fuzzy logic reasoning in order to investigate how much the central bank's announcements matter on a financial market.

The design of the prediction systems for financial markets and the analyses of performance of trading strategies, based on the fuzzy logic rules, neural networks, pattern recognition techniques or other artificial intelligence methodologies, have been subject of research in the existing literature, which expanded during the past two decades.[1]

In particular, the stock trading expert systems (STESs), which have been proposed in the previous literature, utilize the methods of rule-base evidential reasoning relying on the combination of the fuzzy sets theory (FST) tools and the Dempster–Shafer theory (DST) outlined in the seminal works by Dempster (1967, 1968) and Shafer (1976). In financial markets applications, where in the decision

[1] In addition, new techniques have also been introduced more recently in this type of analyses, which includes e.g. machine learning (see e.g. Hsu et al. (2016), Huck (2019) and Kyriakou et al. (2019), among others).

support systems the outputs are typically defined as the labels of the actions (or decisions, such as ‘buy’ or ‘sell’ signals to trade a particular financial asset), the traditional methods based on conventional fuzzy logic cannot be directly employed (see: Dymova et al. (2012)). In this instance, the RIMER (Rule-based Inference Methodology Using the Evidential Reasoning) approach of Yang et al. (2006 and 2007), relying on the evidential reasoning described by Yang (2001) and Yang and Xu (2002a and 2002b) that exploits the belief rules systems (Hodges et al. (1999) and Parson (1996)), has been explored as the more appropriate solution. In case of the financial market investments, the traditional *“IF – THEN”* rules constitute natural decision-making tools used in practice by investors. From the methodological point of view, they may be treated as special cases of more general belief rule systems (see more detailed discussion in Dymova et al. (2012)). The knowledge-based systems relying on human knowledge in form of the *“IF – THEN”* rules have also been considered as the most visible and fastest growing branch of artificial intelligence (Yang et al. (2006)). Therefore, in our study we apply the *“IF – THEN”* rules in the design of our proposed rule-based trading strategy, which exploits the data from 3 segments of the broader financial market (stock market, foreign exchange market and bonds market)[2] combined with the information released on regular basis by the central bank about its monetary policy decisions.

The existing literature regarding the rule-based trading systems implemented on financial markets has been focused so far on a variety of different predictors of

[2] Most of the studies from this area concern predominantly stock market (see e.g. Lee and Jo (1999), Leigh et al. (2002), Chang and Liu (2008), Boyacioglu and Avci (2010), Dymova et al. (2010), Teixeira and De Oliveira (2010), Dymova et al. (2012), Cervelló-Royo et al. (2015), Hafezi et al. (2015), Sheta et al. (2015), Göçken et al. (2016), Chang et al. (2016), Chourmouziadis and Chatzoglou (2016), Rubell and Jessy (2016), Arévalo et al. (2017), Beyaz et al. (2018), Chatzis et al. (2018), Tsinaslanidis (2018), Brzeszczyński and Ibrahim (2019) and Sant’anna et al. (2020)), while substantially fewer papers deal with other segments and instruments, such as bonds market and interest rates (see Kim and Noh (1997) and Nunes et al. (2019)) or foreign exchange market (see e.g. Deng et al. (2015)). Hence, our paper provides a much more comprehensive evidence from 3 market segments reported in one compact study.

asset prices, however it largely overlooks the role of central banks and their public announcements, which are often a direct cause of price movements of financial instruments. In this paper, we fill this literature gap.

Central banks' communication, and its impact on financial markets, was however analysed in different contexts in the studies using typically the data from the US and the European Union relying mainly on the Federal Reserve Board (FED) and the European Central Bank (ECB) monetary policy decisions (see the evidence published in Bernanke and Kuttner (2005), Wongswan (2009), Hausman and Wongswan (2011), Bekaert, Hoerova and Lo Duca (2013), Lucca and Moench (2015) and more recently in Cieslak, Morse and Vissing-Jorgensen (2020), among others). There exist also related papers on the role of central banks' public announcements and their influence on asset returns in emerging markets countries, although they are relatively scarce and they also tend to concern the stock market.[3]

In summary, performance of rule-based trading systems relying on the information released by central banks constitute a clear gap in the literature.

Given that most of the related studies, which focus on the impact of central banks announcements, present mainly the results using the data from stock markets, our research contributes, therefore, to the current pool of knowledge not only in terms of providing novel evidence about the performance of a rule-based trading system, but also through the results using in one compact study a comprehensive dataset from three most important market segments. Previous evidence using the data from Poland points towards the existence of the statistically significant responses of the Polish financial market in these three sectors (see Brzeszczyński and Kutan (2015),

[3] See, for example, Robitaille and Roush (2006), Hanousek, Kočenda and Kutan (2009), Serwa (2006), Büttner and Hayo (2012), Su, Ahmad and Wood (2020), Sun (2020), Frömmel, Han and Gysegem (2015), Baranowski and Gajewski (2016), Brzeszczyński, Gajdka and Kutan (2017) and Brzeszczyński and Kutan (2015).

Brzeszczyński et al. (2017) and most recently Brzeszczyński et al. (2020)). Therefore, in this paper we explore those effects more extensively and we empirically address the question about how much the central bank's announcements matter on a financial market by applying the rule-based trading system approach in the design of an investment strategy and by simulating trades to quantify their profitability in the out–of–sample period using the data from a broad financial market in Poland (spanning across the above mentioned 3 segments and a total of 12 instruments).

To the best of our knowledge, our paper is the first such study using central bank's data about monetary policy announcements in the rule-based trading system, which also proposes a trading strategy in the out-of-sample periods relying on the in-sample estimations in order to predict the prices of financial market instruments. The obtained results allowed to precisely answer the question formulated in the title of this paper and delivered the knowledge, which is not only important from purely academic point of view, but it also has very practical implications for e.g. financial market investors and other financial market analysts etc.

The findings from this paper have broader meaning not just for the market in Poland, but for other international markets as well. Using the example of Poland, as a large European emerging financial market (and, at the same time, also the biggest European Union (EU) market with independent central bank and its own national currency), our approach may be applied also in case of other European emerging markets and other international markets, where central banks announcements are different in terms of their frequency etc. than those in e.g. more advanced economies. At the same time, it needs to be emphasized that the National Bank of Poland has been conducting very transparent communication policy with financial markets, which makes it a valuable subject to study.

Another reason why the results relying on the data from Poland, and from the Polish central bank, are important is that despite joining the European Union (EU) in 2004, Poland decided to keep it is own national currency (rather than adopt the Euro), which in consequence allowed it to conduct its own monetary policy (executed by the NBP) rather than depend on the monetary policy of the European Central Bank (ECB), which would be the case, if Euro replaced Polish Zloty. This situation also makes Poland a unique market to study (not just within the EU, but also from the more global perspective).

In summary, the experience of the Polish central bank can serve as an example for other international markets, which have been implementing important economic reforms and which have been following similar path as Poland.

Last but not least, the design of our methodology allows also to analyse market efficiency by using such important tool as the rule-based trading system, which has been rarely exploited so far in the literature focused on efficient markets research (and, in particular, not in the context of central banks actions and their communication policies etc.).[4]

The remainder of this paper is organized as follows. Section 2 describes the database and the sample period. Section 3 discusses the methodology. Section 4 presents the performance of the proposed rule-based trading system in the out–of–sample period relying on the in–sample estimations. Additional robustness analysis is reported in Section 5. Section 6 provides a discussion, while the last section 7 concludes.

[4] By using the rule-based trading systems, the analyses of market efficiency can directly explore and capture the reactions of financial instruments from different segments of a broader financial market to the announcements of new information revealed by central banks (as well as quantify the profit opportunities that may be achieved by investors in different market segments that we investigated in our study, which are characterized by different levels of trading volume and liquidity etc.).

2. Data and Sample Period

The sources of data, which we exploited for construction of the database used in this study, are: National Bank of Poland (information about the NBP announcements dates and the values of the newly revealed data) and Bloomberg (data about prices from the foreign exchange market, bonds market and stock market).

Our data sample covers over 10–years long period from 6th November 2009 to 15th February 2020.

In order to test the proposed rule-based trading system in practice, we distinguish the in–sample estimation period, which ends on 24th May 2019 and which includes a total of daily 2491 observations, as well as the out–of–sample period, which spans from 25th May 2019 to 15th February 2020.

The frequency of data is daily and we additionally included the intra-daily data (at 1-hour, 30-minutes and 1-minute frequencies) in the presented out–of–sample analyses.

For the purpose of the design of our rule-based trading strategy, we first constructed regression models for 12 financial instruments from 3 most important market segments on the broader financial market in Poland: stock market (stock indices: WIG, WIG20 and sWIG80), foreign exchange market (currency exchange rates: USD/PLN, EUR/PLN, GBP/PLN, CHF/PLN and JPY/PLN) and bonds market (1–year bonds, 2–years bonds, 5–years bonds and 10–years bonds).

Indices WIG, WIG20 and sWIG80 are traded on the Warsaw Stock Exchange (WSE). WIG is a broad market index, WIG20 is a ‘blue chip stocks’ index of the 20 largest firms and sWIG80 is an index of small firms. In the bonds market, we examined the treasury bonds with four most important maturities (from 1 year to 10 years). Bonds in Poland are also traded at the WSE. In case of the foreign exchange market, we used the largest currency pairs for the rates against the Polish zloty (PLN) defined as the number of units of the PLN per one unit of the foreign currency. These instruments are traded on the international currency market.

In the rule-based trading system presented in this paper, we used the following key announcements published by the National Bank of Poland (NBP) regarding the release of its new monetary policy data: (1) interest rate, (2) money supply, (3) official reserves and (4) current account data.

The NBP announcements are captured by the binary dummy variables coded for the days when the particular news events occurred. They are designed for the following four situations: when there was an increase or decrease of the particular variable and when the announced new value was above or below the market expectations (measured using the data from Bloomberg). Only in case of the official reserves we could create just two binary dummy variables: when their value increased or decreased (because there were no market expectations data available for this specific announcement).

Table 1. Summary of binary dummy variables.

NBP announcements according to types:	Names of dummy variable:
Increase of NBP interest rate	RATE_UP
Decrease of NBP interest rate	RATE_DOWN
NBP interest rate above market expectation	RATE_ABOVE
NBP interest rate below market expectation	RATE_BELOW
Increase of M3 money supply	M3_UP
Decrease of M3 money supply	M3_DOWN
M3 money supply above market expectations	M3_ABOVE
M3 money supply below market expectations	M3_BELOW
Increase of current account value	CURRACCM_UP
Decrease of current account value	CURRACCM_DOWN
Current account value above market expectations	CURRACCM_ABOVE
Current account value below market expectations	CURRACCM_BELOW
Increase of international reserves	RESER_UP
Decrease of international reserves	RESER_DOWN

A summary of the announcements used to code the binary dummy variables is presented in Table 1. It shows that collectively there were 450 events in form of the NBP news releases mentioned above during the entire period of the in–sample analysis with the following numbers of the binary dummy variables: 105 for interest rates, 115 for money supply, 115 for current account and also 115 for official reserves.

Table 2 shows a further summary of these events, whereas Table 3 reports the types of changes of the NBP data.

Table 2. NBP interest rate and other macroeconomic data announcements in the in–sample period from 6th November 2009 to 24th May 2019

Announcements and the timing of their publication:		Number of announcements:
Interest rate	Announcement after the decision of the Monetary Policy Council	105
Money Supply (M3)	Usually 12th–14th calendar day of every month	115
Current Account	Usually middle of every month	115
Official Reserves	Usually 5th–7th calendar day of every month	115

Source: National Bank of Poland and authors' own calculations.

Table 3. Changes of the NBP interest rate and other macroeconomic data announcements in the in–sample period from 6th November 2009 to 24th May 2019

	Interest rate	Money Supply (M3)	Current Account	Official Reserves
Type of changes:	Number of announcements:			
Total number of changes	15	112	113	115
Change upwards	5	63	62	63
Change downwards	10	49	51	52

Source: National Bank of Poland and authors' own calculations.

In order to understand properly the NBP data, which we used in this study, we explain below first more generally the policy of the Polish central bank and, subsequently, we discuss the advantages and disadvantages of using the data from the National Bank of Poland.

The stability and the changes of central banks policies can be considered from the following two points of view.

First, this issue may concern the general principles governing the monetary policy in a given country, which in practice change very rarely. In Poland such situation occurred only once during the last two decades. Until year 2003, the National Bank of Poland conducted its monetary policy according to the recommendations of the Monetary Policy Council (a council which is part of the NBP central bank and which is composed of economic experts), where the basic goal was defined as maintaining price stability. The role of the NBP was to pursue direct inflation targeting. From the beginning of the year 2004, the NBP policy changed and the continuous inflation target was adopted (at 2.5% level with a permissible fluctuation band of +/- 1 percentage point, which means that every month the annual consumer price index (CPI) value should be as close as possible to 2.5%). There was no further change of the NBP policy after the year 2004, so the sample period in our study was not affected in any way by any policy shifts.

Second, the issue of the frequency of the policy decisions execution may also concern the frequency and number of the central banks monetary policy councils meetings during the year and the frequency of publication of the central banks data. In Poland the NBP central bank has been executing transparent communication policy with financial markets since the year 2000, when publication of monetary policy data started on regular basis, i.e. every month. The main NBP body responsible for monetary policy in Poland, i.e. Monetary Policy Council which is chaired by the NBP president, holds 11 meetings a year when monetary policy decisions are made (and there is one additional meeting in summer but without issuing monetary policy decisions). In comparison, the Federal Reserve Board (FED) in the USA holds 8 meetings a year, the European Central Bank (ECB) has 8 meetings a year (with the Governing Council's monetary policy meetings every 6 weeks), the Bank of Japan has 8 meetings a year and Swiss National Bank holds only 4 meetings a year. Therefore, the frequency of the Polish central bank's monetary policy council meetings is higher than in case of central banks in the above mentioned major economies so its announcements, mostly issued monthly, are typically more closely connected with the latest monetary decisions than announcements of other central banks. However, some selected data in other markets are published with higher frequency than in Poland, such as the elements of the US money supply data or the US international reserve position etc.

Regarding the advantages and disadvantages of using the data from the National Bank of Poland, transparency as well as regularity and relatively high frequency of publication are its main advantages. It needs to be mentioned also that the quality of the NBP data follows the European Union standards, which is an important benefit too. The disadvantages are similar to the shortcomings of central banks announcements in most other countries. For example, in many developed and emerging markets around the world there exist problems connected with the shadow economy and the shadow economy activity usually cannot be precisely reflected in the central banks statistical data (in Poland shadow economy is estimated to account for about 10% of the GDP[5], which is higher than the corresponding figures for most

[5] See the Ernst & Young (EY) report about the grey economy in Poland available at: https://assets.ey.com/content/dam/ey-sites/ey-com/en_pl/topics/eat/pdf/03/ey-szara-strefa-w-polsce-final.pdf

developed markets, but lower than the share of the shadow economy in most other emerging markets).

In the next section we describe and discuss our methodology.

3. Methodology

We propose in this paper a rule-based trading strategy relying on the signals extracted from the NBP central bank's announcements regarding its monetary policy decisions.

This approach is conceptually close to some fuzzy expert systems (see e.g. Dymova et al. (2012) or Rubell and Jessy (2016), among others) and the stock market investment strategies based on rule-based reasoning (see e.g. Brzeszczyński and Ibrahim (2019)).

In our study, we adopt the framework of the rule-base evidential reasoning following Dymova et al. (2012) and we deal with the special case of the decision rules of the following general type:

$$IF\ x\ is\ `A'\ THEN\ `B' \quad (1)$$

where *'B'* does not necessarily constitute any real or fuzzy value, but instead it is a *label* denoting a specific action (for example: a 'buy' or 'sell' decision to trade a particular financial asset), which the expert system generates when the *'IF'* condition is met.

Examples of such *"IF – THEN"* rules have been presented in the previous literature in the papers by Dymova et al. (2012)), who adopted 'buy', 'sell' and 'hold' labels, or Brzeszczyński and Ibrahim (2019), who utilized 'buy', 'sell' and 'do not trade' labels in their stock market investment strategies.

In order to identify the NBP announcements for the implementation in our trading strategy, we used GARCH regression models (Engle (1982) and Bollerslev (1986)). Therefore, in the first step we estimated the parameters of the following GARCH(S,Q) models in order to capture the effects of the NBP communication in case of all 12 instruments from all 3 market segments:

$$r_t^i = \beta_0 + \sum_{j=1}^{J} \sum_{k=-K}^{K} \left(\beta_{j,t-k} D_{t-k}^j + \delta_{j,t-k} CV_{t-k}^n \right) + \varepsilon_t^i \tag{2}$$

$$h_t^i = \gamma_0 + \sum_{s=1}^{S} \gamma_s \left(\varepsilon_{t-s}^i\right)^2 + \sum_{q=1}^{Q} \varphi_q h_{t-q}^i + \sum_{k=-K}^{K} \lambda_{j,t-k} CV_{t-k}^n + \xi_t^i \tag{3}$$

where:

r_t^i – is the daily rate of return (holding period return) of i–th financial instrument defined as $r_t^i = (p_t^i - p_{t-1}^i)/p_{t-1}^i \cdot 100$ where p_t^i is the price of i–th financial instrument on day t,

D_{t-k}^j – are the binary dummy variables taking on the value of 1 when the given j–th NBP announcement was made and 0 otherwise,

CV_{t-k}^n – are the daily rates of return of control variables n used in individual models,[6]

h_t – is the conditional variance equation,

ε_t^i and ξ_t^i – are respective error terms in equations (2) and (3),

[6] In case of the models for the bonds, the control variable is the Bloomberg Barclays Global Aggregate Total Return Index as the global bond market indicator. For the stock market models, we adopted MSCI World Index as the commonly used measure of the global stock market movements. In the foreign exchange market models, we used the Bloomberg's baskets of global currencies measured against respective currency (EUR, USD, CHF, GBP or JPY).

β_0, $\beta_{j,t-k}$ and $\delta_{j,t-k}$ – are the estimated parameters in equation (2),

γ_0, γ_s, φ_q and $\lambda_{j,t-k}$ – are the estimated parameters in equation (3),

J – is the number of the types of the macroeconomic announcements according to their sub–types (i.e. 'above', 'below', 'up' and 'down'),

-K – is the maximum lag of each j–th announcement,

K – is the maximum lead of each j–th announcement.

The analysis in this paper deals with very short–term effects and, therefore, in equation (2) the maximum lag and the maximum lead (k = -$K,...,0,...,K$) are restricted to +/- 3 days, so: k = -3, -2, -1, 0, 1, 2, 3.

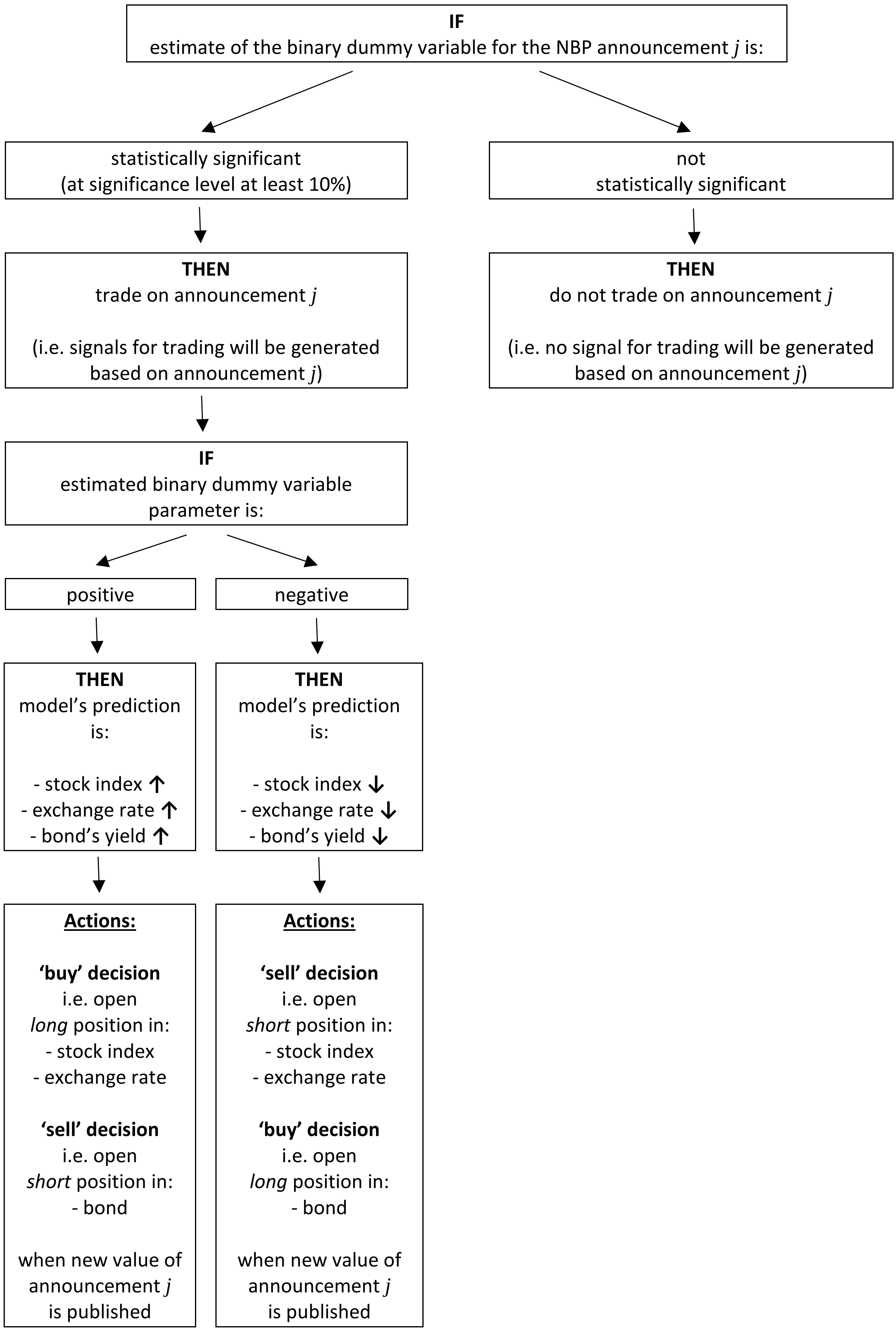
The main focus of our investigation using model (2) – (3), and in further development of the proposed rule-based trading system, are the estimates of the binary dummy variables parameters: $\beta_{j,t-k}$.

In the models where there was persistent heteroscedasticity, we exploited higher orders of GARCH than GARCH(1,1) specification, i.e. GARCH(2,1), GARCH(1,2), GARCH(2,2) etc. When the asymmetric effects were present, we used alternative other versions, such as EGARCH, GJR-GARCH etc. If autocorrelation existed, it was dealt with by adding the AR and/or MA terms.

In the next step, we designed a trading strategy, which relies on the rule-based reasoning and which exploits the *"IF–THEN"* decision rules. Its general structure is shown in Figure 1.

More specifically, our investment strategy is simulated according to the procedure with the following trading rules of the *"IF x is 'A' THEN 'B'"* type mentioned earlier. It is also important to emphasize that the 'buy' and 'sell' decisions are designed differently for stock market and currency market instruments than for bonds.

Figure 1. Decision rules applied in the design of the trading strategy



In case of stock indices and foreign exchange rates, the 'buy' decision is triggered on the day when there is the NBP monetary policy announcement, which was statistically significant (at the level at least $p < 0.10$) and had a positive sign. The 'sell' decision is induced when there is an announcement that was statistically significant (also at the level at least $p < 0.10$) and had a negative sign.

In case of bonds, the models (2) – (3) in the in–sample period analysis are constructed using their yields as the dependent variable, while in the proposed trading system the buying and selling transactions are executed based on their prices, so the signals to trade must in fact predict bonds price changes. Therefore, the negative sign of the estimated coefficient means the decrease of the bond's yield, but if the bond's yield goes down, its price goes up, so in such situation a 'buy' decision is triggered. If the estimated parameter has positive sign, then the increase in bond's yield is predicted, which implies a decrease of its price, so a 'sell' decision is triggered.[7]

According to our trading rules, the positions are closed at the end of the investment horizon, i.e. at the end of day $t+1$. Due to the fact that the NBP announcements were released always in the afternoon at 2:00 p.m., i.e. soon before the market activity slows down and before it closes on day t (the trading session at the Warsaw Stock Exchange terminates at 5:00 p.m.), we concentrate mainly on the evaluation of the performance of the strategy during the next day $t+1$, although we also report the results on day t from 2:00 p.m. until the end of the day at 5:00 p.m.

Next section presents the results of the trading strategy based on the rules described above, which rely on the estimates of the binary dummy variables parameters from models (2) – (3) for all 12 instruments.

[7] This mechanism in the bonds market is defined by the inverse relation between a bond's price and its yield in the bond's pricing model.

4. Results

The first stage in our analysis was to obtain the estimates of the binary dummy variables from the regression model (2) – (3) for all 3 market segments covering all 12 instruments in our sample period.

For the purpose of designing the trading strategy based on trading rules, presented and discussed subsequently in this section, the most relevant specifications in practice are those from the models with the lag *t–1* (i.e. representing 1 day lag). We also focus below only on the changes of the new macroeconomic data revealed by the NBP, because the proposed strategy relies on this type of signals. Estimation results for the relevant parameters from equation (2) are reported in Table 4.

As Table 4 shows, we identified the following statistically significant estimates of coefficients $\beta_{j,t-1}$ in the process of estimation of equation (2) for lag *t–1*, which capture the changes of the following variables: change of interest rate downwards in 2-years bond model ($\beta_{j,t-1}$ = 0.023779 and significant at 1% level), change of interest rate downwards in 5-years bond model ($\beta_{j,t-1}$ = 0.013230 and significant at 1% level), change of official reserves downwards in 5-years bond model ($\beta_{j,t-1}$ = -0.002568 and significant at 10% level), change of current account upwards in 10-years bond model ($\beta_{j,t-1}$ = -0.003910 and significant at 10% level), change of interest rate downwards in USD/PLN currency exchange rate model ($\beta_{j,t-1}$ = 0.002846 and significant at 10% level), change of interest rate downwards in CHF/PLN currency exchange rate model ($\beta_{j,t-1}$ = 0.002787 and significant at 10% level), change of interest rate downwards in GBP/PLN currency exchange rate model ($\beta_{j,t-1}$ = 0.002787 and significant at 5%

level), change of interest rate upwards and downwards in JPY/PLN currency exchange rate model ($\beta_{j,t-1}$ = -0.003770 and significant at 10% level and $\beta_{j,t-1}$ = 0.004354 and significant at 5% level, respectively) and change of M3 money supply downwards in WIG20 index model ($\beta_{j,t-1}$ = 0.005813 and significant at 5% level).

Hence, there appear to be only 10 instances of statistically significant estimates out of the investigated 96 binary dummy variables (i.e. 12 instruments x 4 announcements x 2 types of possible changes upwards or downwards = 96 dummies estimates), which constitutes about 10% of all cases. However, given that these NBP announcements proved to matter in the past years, they are also the most relevant ones to use in the design of the trading system based on the adopted decision rules. Therefore, we exploit and investigate this particular group of variables further below in this section.

The trading strategy is executed in the out–of–sample period from 25th May 2019 to 15th February 2020. The estimates from model (2) – (3) were determined in the in–sample period covering 6th November 2009 - 15th February 2020. Both the in–sample estimations and the out–of–sample analyses were performed based on daily data frequency and, additionally, the trading strategy was further investigated using high-frequency observations at 1-hour, 30-minutes and 1-minute intervals.

Table 4. Estimation results of parameters $\beta_{j,t-1}$ from equation (2) for lag t–1
for the upward and downward changes of the NBP announcements

	Announcement:							
	Interest rate		Money supply		Current account		Official reserves	
	Change up	Change down	Change up	Change down	Change up	Change down	Change up	Change down
Stock Market								
WIG	0.002109 (0.003505)	0.003962 (0.003328)	0.002054 (0.002001)	0.003894 (0.002431)	-0.002225 (0.002458)	-0.000582 (0.002584)	-0.000953 (0.001339)	0.000226 (0.001197)
WIG20	0.002013 (0.004297)	0.004579 (0.003601)	0.003595 (0.002215)	0.005813 ** (0.002720)	-0.001473 (0.002987)	-0.000175 (0.003179)	-0.001035 (0.001511)	0.000624 (0.001382)
SWIG80	0.001048 (0.005000)	0.001663 (0.002213)	0.000855 (0.001655)	0.000659 (0.001804)	-0.001437 (0.001160)	0.000106 (0.001458)	-0.000059 (0.000784)	-0.001248 (0.000808)
Foreign Exchange Market								
USD/PLN	-0.002732 (0.003816)	0.002846 * (0.001704)	-0.001753 (0.001638)	-0.002315 (0.001599)	0.000671 (0.000920)	-0.000591 (0.001457)	-0.000581 (0.000731)	-0.000325 (0.000585)
EUR/PLN	-0.001313 (0.002479)	0.001339 (0.001765)	0.000027 (0.000675)	-0.000320 (0.000520)	-0.000960 (0.000702)	-0.000583 (0.000775)	-0.000117 (0.000423)	-0.000319 (0.000368)
GBP/PLN	-0.002705 (0.003362)	0.002945 * (0.001608)	-0.001540 (0.001321)	-0.001921 (0.001291)	-0.000887 (0.000796)	-0.001091 (0.001029)	-0.000281 (0.000701)	0.000013 (0.000584)
CHF/PLN	-0.003763 (0.003419)	0.002787 * (0.001685)	-0.001145 (0.001220)	-0.001269 (0.001131)	0.000610 (0.000862)	-0.000360 (0.001249)	-0.000684 (0.000655)	0.000575 (0.000541)
JPY/PLN	-0.003770 * (0.002242)	0.004354 ** (0.001829)	-0.001347 (0.002184)	-0.002137 (0.002095)	0.000884 (0.001234)	0.000434 (0.001571)	-0.000263 (0.000787)	0.000375 (0.000711)
Bonds Market								
1-year bond	-0.006788 (0.012468)	0.010197 (0.008385)	0.002050 (0.012972)	-0.000017 (0.013023)	0.003944 (0.005914)	0.003610 (0.006751)	0.000362 (0.002648)	0.000751 (0.003428)
2-years bond	0.003074 (0.012159)	0.023779 *** (0.003361)	-0.005623 (0.003785)	-0.003074 (0.003522)	0.002078 (0.003251)	0.000307 (0.003480)	0.000399 (0.001998)	-0.002154 (0.001932)
5-years bond	-0.001738 (0.004680)	0.013230 *** (0.003292)	-0.002188 (0.003935)	-0.000751 (0.003769)	-0.001527 (0.003254)	-0.001971 (0.003308)	-0.000694 (0.001135)	-0.002568 * (0.001465)
10-years bond	0.006409 (0.004331)	0.000820 (0.006472)	-0.000886 (0.003096)	0.000120 (0.003247)	-0.003910 * (0.002164)	-0.002252 (0.002617)	-0.001519 (0.001459)	0.000352 (0.001713)

Notes: (1) Standard errors are reported in brackets. (2) Statistical significance of the estimated parameters is indicated as follows: *** – statistically significant at 1% level, ** – statistically significant at 5% level and * – statistically significant at 10% level.

Figure 1 illustrates the trading rules applied in the design of our investment strategy relying on the binary dummy variables from model (2) – (3), which capture the impact of the NBP communication of the new monetary policy announcements on the movements of the assets' prices. Given that we detected evidence of appreciation and depreciation effects, as a direct response of the financial markets in its all 3 segments to the NBP monetary policy decisions, we investigated if such events as the release of new data by the central bank may create profit opportunities for the financial market investors.[8] Following the rules depicted in Figure 1, we analysed the possible profits and losses from trades based on the statistically significant estimates (at the level at least $p < 0.10$) of the binary dummy variables lagged by one day (i.e. for lag t *-1*) in models (2) – (3).

As mentioned earlier, the NBP announcements were always made in the afternoon at 2:00 p.m., so for the out–of–sample strategy evaluation we used the intra–daily frequency data, because in reality the traders are likely to transact within rather

[8] Note that the notions 'positive' or 'negative' shown in Figure 1 are related to the signs of the estimated dummy variables parameters in the model presented in equation (2) for the statistically significant dummy variables capturing relevant NBP central bank's announcements. The positive or negative sign means, respectively, positive or negative impact on the returns of the stock market indices, on the returns of the foreign exchange rates and on the yields of bonds in the individual models. If the estimated parameter has positive sign, it implies an increase of the returns of the stock market indices and foreign exchange rates and an increase of bonds yields (which in case of bonds means a prediction of the decrease of bonds prices). Therefore, according to the *"IF – THEN"* decision rule, this situation respectively further implies buying. i.e. opening long positions in stock market indices and in foreign exchange rates, or selling, i.e. opening short positions in bonds. In case when the estimated parameter has negative sign, the above relations are exactly opposite and, hence, the opposite transactions are implied. Although this mechanism depends on the particular financial instruments, the design of models (2) – (3) and the specific relations within the broader *"IF – THEN"* rule-based trading system proposed in this paper, it needs to be mentioned that it is also indirectly related to the concept of 'risk on' or 'risk off' markets as a whole. The 'risk on' environments are characterised by a combination of expanding corporate earnings, optimistic economic outlook, but also accommodative central bank's policies etc. We can, therefore, also assume that a growing stock market is a 'risk on' sign. As investors feel that the market is being supported by strong economic fundamental data, including supportive central bank's policy, they perceive lower risk in the market and in its outlook. Conversely, 'risk off' environments are caused by widespread corporate earnings downgrades, pessimistic economic outlook as well as uncertainty regarding the central bank's policy etc. Our results can be, therefore, regarded also as indirectly indicative of the 'risk on' or 'risk off' environments whenever they show, for example, prediction of increase or decrease of the stock market index returns or prediction of strengthening or weakening of the domestic currency. When stock market rises, there is a 'risk on' environment, while a drop in the stock market means a 'risk off' environment (because investors want to avoid risk and they are averse to it). We thank the anonymous Reviewer for pointing out this issue.

short time horizons in response to such news as public information contained in the central bank announcements and any such analysis should consider investment horizons finer than just 1 day intervals (see Brzeszczyński and Kutan (2015)).

We examined the results of the proposed trading strategy for a variety of different investment horizons at 1–hour intervals, which allows us to present a broad spectrum of very detailed results. The trading horizons are the intervals of time *between* the NBP announcements (made always at 2:00 p.m.) *and* the following points of time denoted in Table 5 as: '+1 hour', '+2 hours', '+3 hours (i.e. end of day t)' for day t and from '+19 hours' to '+27 hours (i.e. end of day $t+1$)' for day $t+1$.

Given that the in–sample estimations cover the period until 24th June 2019, the out–of–sample analysis starts on 25th June 2019 and it includes over 7 months ending on 15th February 2020.

During the entire out–of–sample period there were no interest rate changes made by the NBP in Poland, so in the trading strategy we could not use this particular type of announcement, however we could exploit the information about the publication of other monetary policy data. Ultimately, we have identified 11 announcements in the out–of–sample period, which include: decrease of M3 money supply, increase of official reserves and increase of current account, i.e. there is a total of 11 events in the bonds market and in the stock market.

Table 5 presents a broad spectrum of returns from our investment strategy by instrument types for trades that are executed based on the rules described above.

The returns in Table 5 (and also later in the subsequent Tables 6, 7, 8 and 9) are calculated based on 1-minute frequency data. For the intra-daily prices, and for t denoting 1-minute intervals, they are determined using the following formula:

$$ {}^{(dd@hh:mm)}_{(DD@HH:MM)}r_t^i = (p^i_{t(DD@HH:MM)} - p^i_{t(dd@hh:mm)})/p^i_{t(dd@hh:mm)} \cdot 100 \qquad (4) $$

where $p^i_{t(DD@HH:MM)}$ and $p^i_{t(dd@hh:mm)}$ are the prices of i–th financial instrument at two different points of time $MM:MM$ and $hh:mm$, respectively, with HH and hh denoting hour of the day and MM and mm denoting its specific minute, while DD and dd indicate the date(s) of the particular day(s) on which the return ${}^{(dd@hh:mm)}_{(DD@HH:MM)}r^i_t$ is calculated.

For example, the return in the period from 2:00 p.m. to 5:00 p.m. on 7th February 2020 (using time notation: 14:00 hours and 17:00 hours) is computed as:

$${}^{(07Feb2020@14:00)}_{(07Feb2020@17:00)}r^i_t = (p^i_{t(07Feb2020@17:00)} - p^i_{t(07Feb2020@14:00)})/p^i_{t(07Feb2020@14:00)} \cdot 100.$$

In case of the intra-daily periods spanning across two days, the returns are defined in the same way as in (4) but with DD and dd indicating particular two dates of those different days.

For example, the return in the period from 3:30 p.m. on 5th December 2019 to 11:30 a.m. on the next day 6th December 2019 (using time notation: 15:30 hours and 11:30 hours) is consequently computed as:

$${}^{(05Dec2020@15:30)}_{(06Dec2020@11:30)}r^i_t = (p^i_{t(06Dec2020@11:30)} - p^i_{t(05Dec2020@15:30)})/p^i_{t(05Dec2020@15:30)} \cdot 100.$$

In Tables 5, 7, 8 and 9 the above returns are averaged (for respective types of instruments or days of the week etc.) while in Table 6 they are reported as differences between specific time points across a variety of 30-minutes intervals.

The results in Table 5 demonstrate that such strategy would be profitable in most cases in all the reported investment horizons on day $t+1$, but it would lead to losses on day t. The average loss from the combined strategy for all 11 trades in the last column of Table 5 at 5:00 p.m. on day t is -0.04%. Therefore, it is evident that the profits only materialize on day $t+1$.

As the last column in Table 5 shows, the average profit from the combined strategy for all 11 trades jumps rapidly to 0.09% during the 1–hour interval between the opening of the market at 9:00 a.m. and 10:00 a.m. on day $t+1$. Subsequently, it grows gradually to its highest value of 0.13% at 4:00 p.m. and then drops to 0.09% at the market close at 5:00 p.m.

At the end of day *t+1*, the individual trades for all 11 events are profitable in 8 out of 11 cases, which means 72.7% success ratio. The overall profitability across all events and all trading horizons is positive for 7 out of 11 events, i.e. in 63.6% cases.

Table 5. Performance of trading strategy by instrument types in the out–of sample period from 25th May 2019 to 15th February 2020 on days *t* and *t+1*

Trading horizon on day *t* from NBP announcement at 2:00 p.m. CET on day *t* at time (CET):	**Profit / loss for trades for all the events on day *t***			
	Performance of trades by instrument types (average returns for each instrument type) and overall average:			
	10-years bond	5-years bond	WIG20 index	Overall average for all trades:
3:00 p.m. (+1 hour)	0.01%	-0.02%	0.25%	0.02%
4:00 p.m (+2 hours)	-0.01%	0.01%	0.06%	0.00%
5:00 p.m. (+3 hours, i.e. end of day *t*)	-0.05%	-0.03%	-0.03%	-0.04%
Trading horizon on day *t+1* from NBP announcement at 2:00 p.m. CET on day *t*:	**Profit / loss for trades for all the events on day *t+1***			
	Performance of trades by instrument types (average returns for each instrument type) and overall average:			
	10-years bond	5-years bond	WIG20 index	Overall average for all trades:
9:00 a.m. (+19 hours)	-0.04%	-0.03%	0.12%	-0.02%
10:00 a.m. (+20 hours)	0.22%	0.02%	-0.36%	0.09%
11:00 a.m. (+21 hours)	0.20%	0.00%	-0.15%	0.09%
12:00 p.m. (+22 hours)	0.21%	0.01%	-0.27%	0.09%
1:00 p.m. (+23 hours)	0.21%	-0.01%	-0.14%	0.10%
2:00 p.m. (+24 hours)	0.21%	0.01%	-0.13%	0.10%
3:00 p.m. (+25 hours)	0.19%	0.05%	0.00%	0.12%
4:00 p.m. (+26 hours)	0.23%	0.07%	-0.24%	0.13%
5:00 p.m. (+27 hours, i.e. end of day *t+1*)	0.16%	0.07%	-0.32%	0.09%
Average for all trading horizons for days *t* and *t+1*:	**0.13%**	**0.01%**	**-0.10%**	**0.07%**

Note: Cells highlighted in grey indicate positive returns in respective time horizons and positive average returns.

This pattern of performance is further illustrated graphically using 1-minute frequency data in Figure 2.

For 10-years bonds and 5-years bonds the strategy would deliver the loss on day t during the interval from 2:00 p.m. until the end of the day at 5:00 p.m., but it is profitable during day $t+1$ from 9:00 a.m. until 5:00 p.m. with the peak at 4:00 p.m. In case of the WIG20 index, the strategy records profits in very short term, i.e. only during the first 2 hours on day t , while during the whole day $t+1$ it delivers the loss. However, it needs to be emphasized that the trades on the WIG20 index constitute only 1 out of the total of 11 trades within the whole strategy in the out–of–sample period, which means that the losses which they generated are more than compensated by the profits from the remaining 10 trades on the bonds market. This result shows, therefore, also the benefit of diversification of investments across different asset classes in the presented trading strategy.

Figure 3 additionally illustrates the pattern of returns of the trading strategy in the out–of–sample period for all 11 trades (sorted from average highest to average lowest) for positions opened on day $t+1$ from 9:00 a.m. until different points of time (in 30-minutes intervals) until the end of day $t+1.$ It shows that all of them are positive at most of the distinguished intra-daily intervals.

Figure 2. Performance of trading strategy in the out–of–sample period from 25th May 2019 to 15th February 2020 on days *t* and *t+1* by instrument types

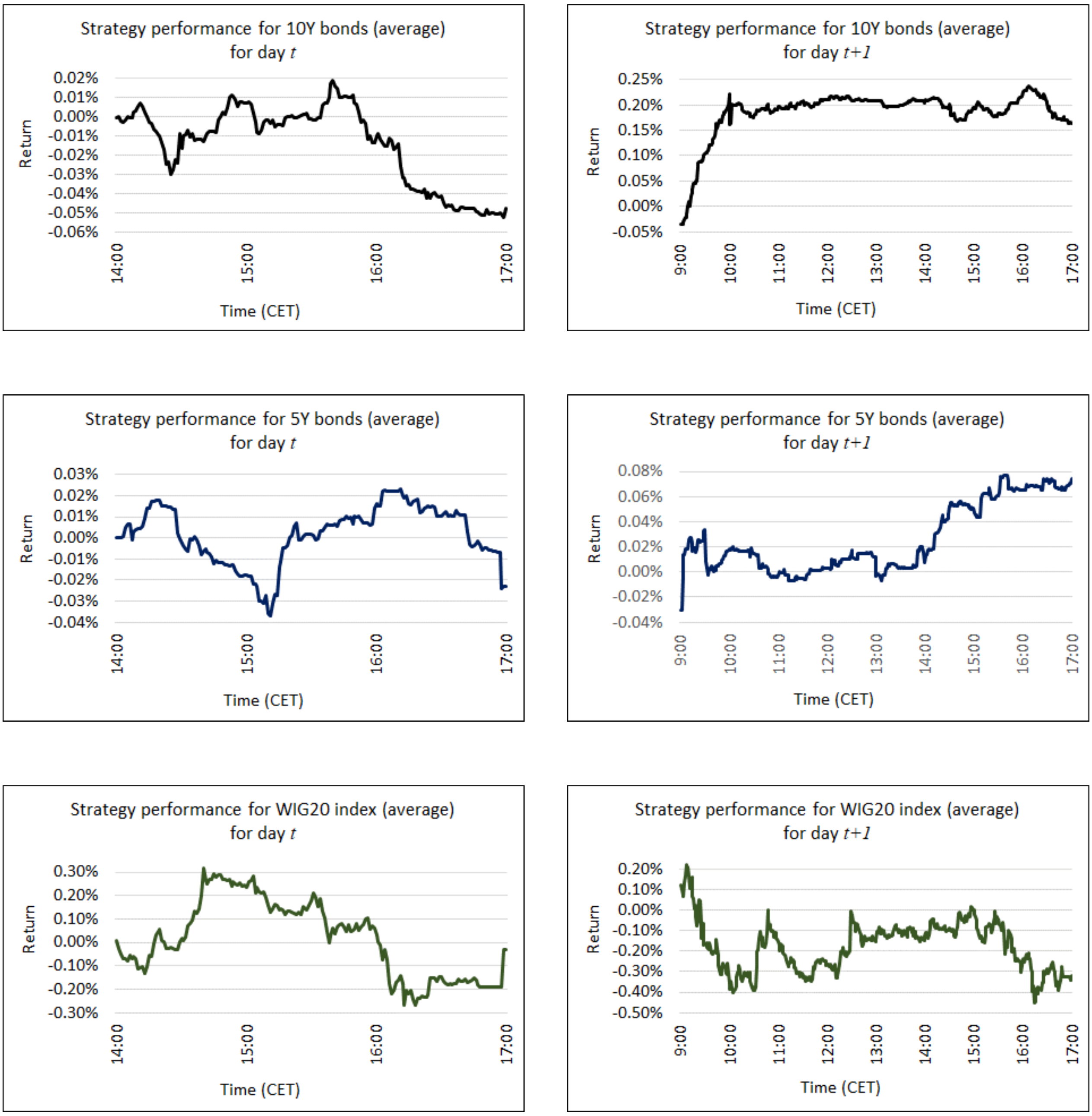
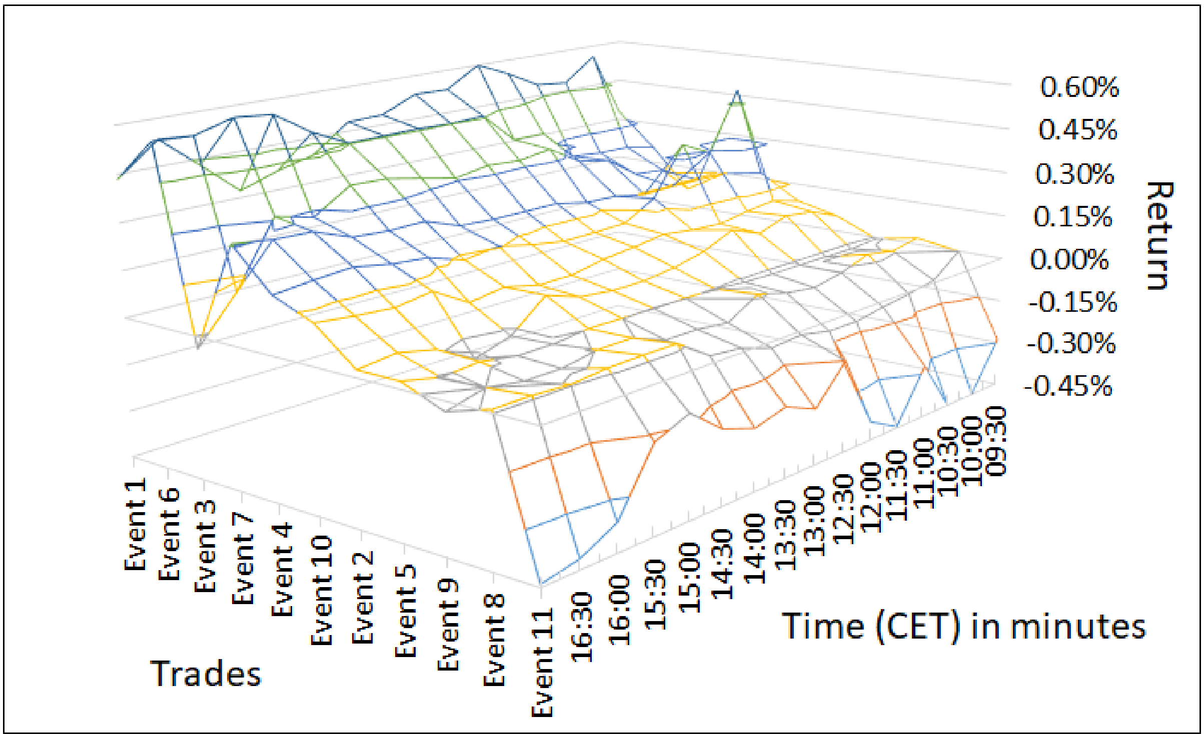


Figure 3. Returns in the out–of–sample period from 25th May 2019 to 15th February 2020 for all 11 trades (sorted from average highest to average lowest) for positions opened on day *t+1* from 9:00 a.m. until different points of time (in 30-minutes intervals) until the end of day *t+1*



We also report the performance of the proposed investment strategy with respect to the inclusion of trading costs, which are in practice necessary in its execution. Costs of trading on financial market are obviously different depending on the specific market segment, particular instrument etc. The typical transaction costs in Poland in the markets investigated in this study (for round-trip transactions, i.e. buying and selling particular assets) are about 0.8% - 0.9% in the stock market, about 0.4% - 0.6% in the bonds market and about 0.02% - 0.05% in the foreign exchange market (see Brzeszczyński et al. (2020)). Because the strategy presented in this paper is very strongly dominated by bonds, the most typical average cost to implement it in practice is around 0.5%.

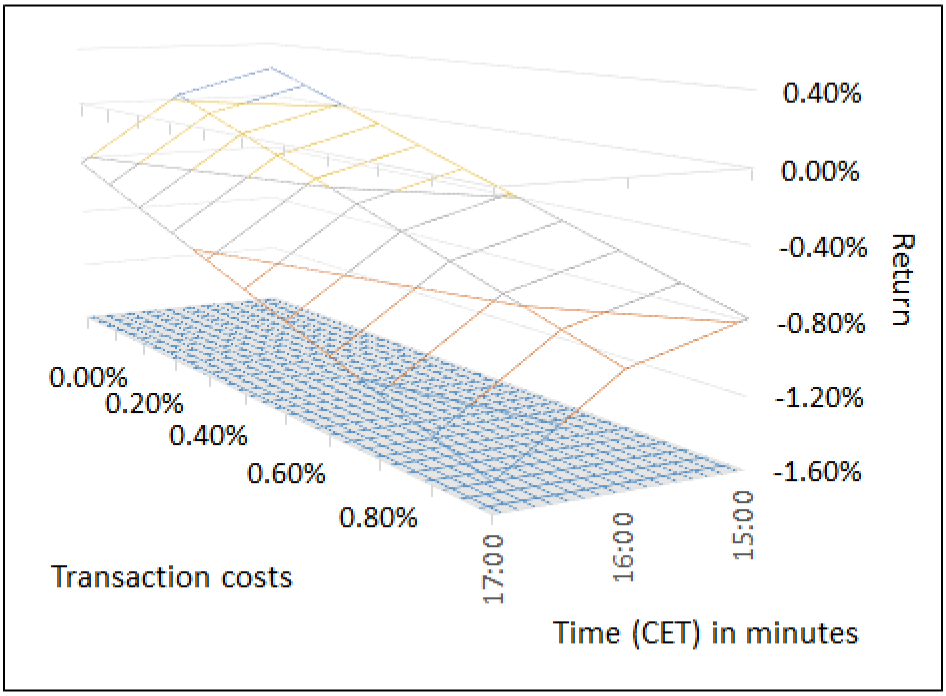
In Figure 4 below we further illustrate a variety of results using a broader interval of possible trading costs in order to reflect the situations when some (usually larger) investors can achieve lower trading cost, while for some other (usually smaller) investors the trading cost can be substantially higher. The graphs in Figure 4 depict the results of the combined strategy, where a typical trading cost is positioned around the middle of the assumed costs spectrum, and demonstrate how it performs on day t and on day $t+1$ when such typical cost deviates upwards or downwards depending on the value of executed transactions, size of the investors (and their overall volume of trade), method of trading etc.

As Figure 4 shows, the performance of the combined strategy with different levels of transaction costs on days t and $t+1$ confirms the same pattern of profitability, as it was indicated already in Table 5, with the best results on day $t+1$, i.e. highlighting the jump between 9:00 a.m. and 10:00 a.m. and the peak at 4:00 p.m. Between 10:00 a.m. and 5:00 p.m. this strategy is robust to trading costs adjustments and it always delivers positive performance even after inclusion of relatively high levels of transaction costs.

We have further investigated the results of our trading strategy on day $t+1$ by calculating the differences in returns for positions opened and closed between different hours on day $t+1$ in 30-minutes intervals.

Figure 4. Performance of the combined trading strategy in the out–of–sample period from 25th May 2019 to 15th February 2020 on day *t* and on day *t+1* with different levels of transaction costs

Performance on day *t*



Performance on day *t+1*

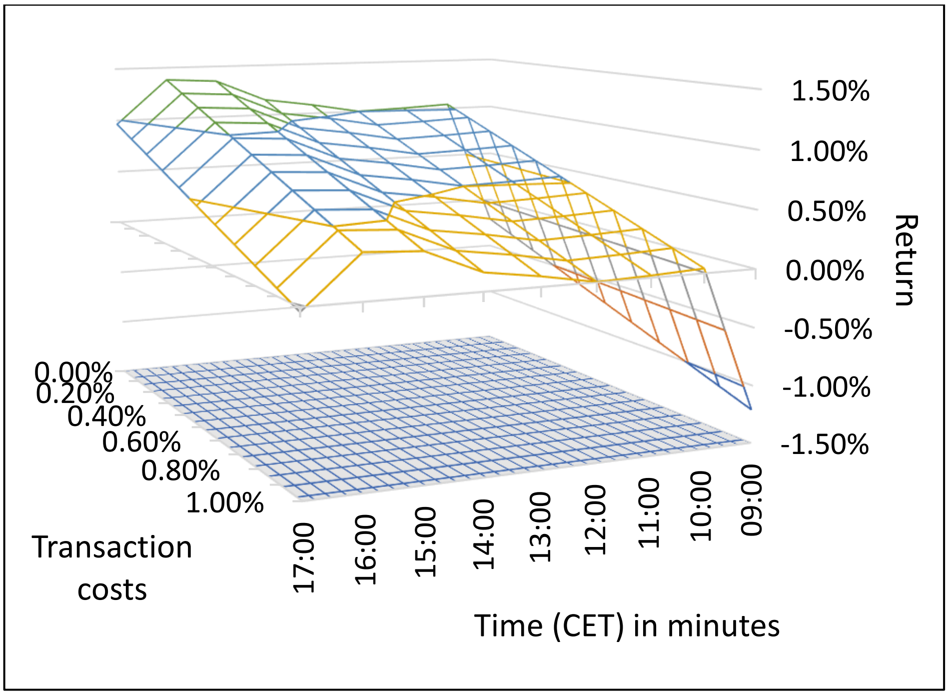


Table 6. Differences in returns of the combined trading strategy in the out–of–sample period for positions opened and closed between different points of time based on 30-minutes intervals (according to CET time) on day *t+1*

Time:	09:30	10:00	10:30	11:00	11:30	12:00	12:30	13:00	13:30	14:00	14:30	15:00	15:30	16:00	16:30	17:00
09:00	0.79%	1.25%	0.96%	1.23%	1.11%	1.21%	1.51%	1.30%	1.32%	1.37%	1.54%	1.57%	1.51%	1.59%	1.44%	1.18%
09:30	0.00%	0.46%	0.17%	0.44%	0.32%	0.42%	0.71%	0.50%	0.53%	0.57%	0.75%	0.77%	0.72%	0.80%	0.65%	0.38%
10:00		0.00%	-0.29%	-0.02%	-0.14%	-0.04%	0.26%	0.05%	0.07%	0.11%	0.29%	0.32%	0.26%	0.34%	0.19%	-0.08%
10:30			0.00%	0.27%	0.14%	0.25%	0.54%	0.33%	0.36%	0.40%	0.58%	0.60%	0.55%	0.63%	0.48%	0.21%
11:00				0.00%	-0.12%	-0.02%	0.28%	0.07%	0.09%	0.14%	0.31%	0.34%	0.28%	0.36%	0.21%	-0.05%
11:30					0.00%	0.11%	0.40%	0.19%	0.21%	0.26%	0.43%	0.46%	0.40%	0.49%	0.33%	0.07%
12:00						0.00%	0.29%	0.08%	0.11%	0.15%	0.33%	0.35%	0.30%	0.38%	0.23%	-0.04%
12:30							0.00%	-0.21%	-0.19%	-0.14%	0.03%	0.06%	0.01%	0.09%	-0.07%	-0.33%
13:00								0.00%	0.02%	0.07%	0.24%	0.27%	0.22%	0.30%	0.14%	-0.12%
13:30									0.00%	0.05%	0.22%	0.25%	0.19%	0.27%	0.12%	-0.14%
14:00										0.00%	0.18%	0.20%	0.15%	0.23%	0.08%	-0.19%
14:30											0.00%	0.03%	-0.03%	0.05%	-0.10%	-0.37%
15:00												0.00%	-0.05%	0.03%	-0.13%	-0.39%
15:30													0.00%	0.08%	-0.07%	-0.34%
16:00														0.00%	-0.15%	-0.42%
16:30															0.00%	-0.26%
17:00																0.00%

Note: Cells highlighted in grey indicate positive returns across respective time horizons according to the following scale: 0%-0.49% (light grey), 0.50%-0.99% (medium grey), 1.00%-1.49% (dark grey) and ≥1.50% (heavy dark grey).

Table 6 shows that if the positions are opened at the beginning of day *t+1* at 9:00 a.m., the highest returns are achieved towards the end of day *t+1* around 3:00 – 4:00 p.m. in the afternoon, but not at the very end of day *t+1* at 5:00 p.m. These results also clearly show that the changes in the effects of the NBP monetary policy announcements between the trading strategies on days *t* and *t+1* manifest themselves most strongly in case of differences between the returns beginning of day *t+1* and the returns achieved on day *t+1* by around 2:00 – 4:00 p.m. (but not at the very end of day *t+1* at 5:00 p.m.).

Figure 5 additionally illustrates the above pattern by depicting the performance of our trading strategy for positions opened between different 30-minutes intervals on day *t+1*.

Figure 5. Performance of trading strategy for positions opened between different 30-minutes intervals on day *t+1*

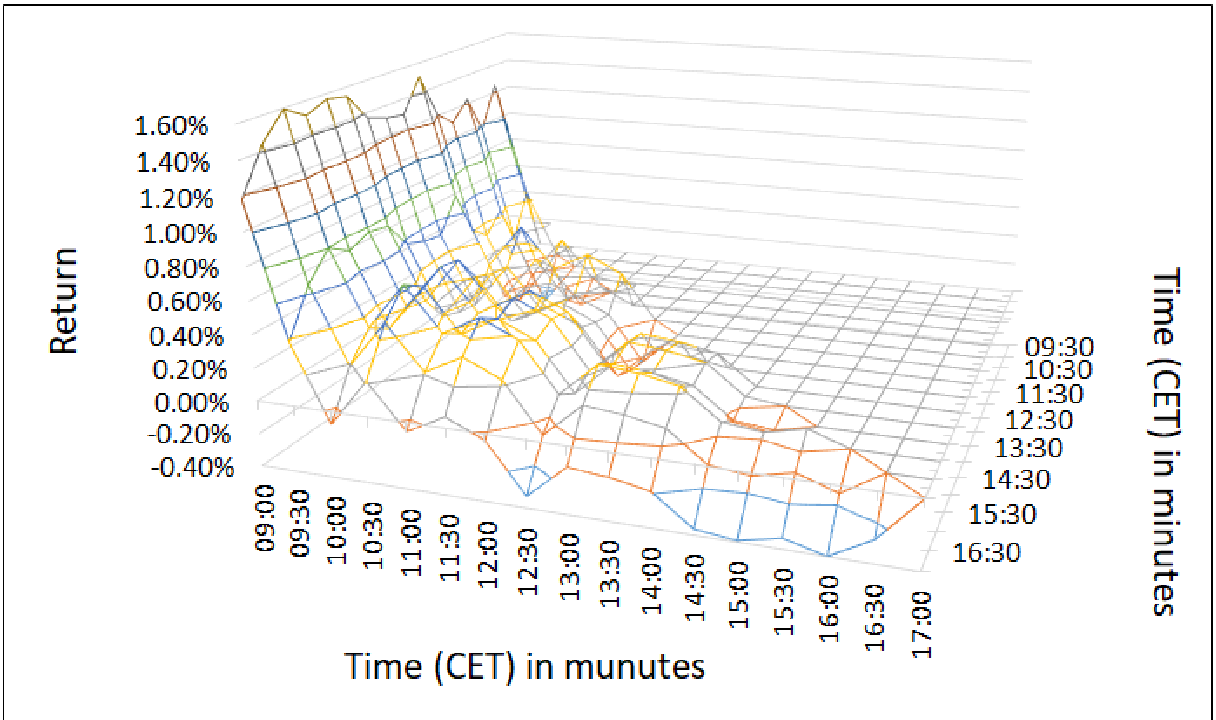


Table 7. Day of the week effects in the performance of investment strategy in the out–of–sample period from 25th May 2019 to 15th February 2020 on days *t* and *t+1*

Trading horizon on day *t* from NBP announcement at 2:00 p.m. CET on day *t* at time (CET):	**Profit / loss for trades for all the events on day *t*** Performance of trades on particular days of the week (average returns):				
	Mon	**Tue**	**Wed**	**Thu**	**Fri**
3:00 p.m. (+1 hour)	0.08%	-	0.03%	0.18%	-0.04%
4:00 p.m (+2 hours)	0.03%	-	0.07%	0.21%	-0.04%
5:00 p.m. (+3 hours, i.e. end of day *t*)	-0.03%	-	0.07%	0.20%	-0.08%
Trading horizon on day *t+1* from NBP announcement at 2:00 p.m. CET on day *t*:	**Profit / loss for trades for all the events on day *t+1*** Performance of trades on particular days of the week (average returns):				
	Mon	**Tue**	**Wed**	**Thu**	**Fri**
9:00 a.m. (+19 hours)	0.02%	-	0.09%	0.19%	-0.09%
10:00 a.m. (+20 hours)	-0.04%	-	0.30%	0.76%	0.00%
11:00 a.m. (+21 hours)	0.04%	-	0.20%	0.69%	-0.01%
12:00 p.m. (+22 hours)	0.02%	-	0.08%	0.80%	0.00%
1:00 p.m. (+23 hours)	0.05%	-	0.09%	0.73%	-0.02%
2:00 p.m. (+24 hours)	0.05%	-	0.13%	0.68%	-0.01%
3:00 p.m. (+25 hours)	0.08%	-	0.18%	0.56%	0.01%
4:00 p.m. (+26 hours)	0.02%	-	0.19%	0.63%	0.04%
5:00 p.m. (+27 hours, i.e. end of day *t+1*)	-0.09%	-	0.18%	0.63%	0.05%
Average for all trading horizons for days *t* and *t+1*:	**0.02%**	-	**0.13%**	**0.52%**	**-0.01%**

Note: Cells highlighted in grey indicate positive average returns in respective time horizons.

Finally, we investigated the day of the week effects in performance of the proposed investment strategy in the out–of–sample period.

The NBP announcements were published on all days of the week, except for only Tuesday, and the trades were executed accordingly on these days. The results for individual days of the week are reported in Table 7, which shows that the strategy was most profitable in the middle of the week, following the announcements made on Wednesdays and Thursdays, while its performance was much worse in case of Mondays and Fridays.

In summary, based on the proposed trading rules, we analysed a variety of different investment horizons within our trading strategy and we detected a clear and consistent pattern of possible profit opportunities for the investors who responded to the NBP central bank's communication in case of news for which there were statistically significant estimates of the NBP announcements binary dummy variables. This is an important finding that has practical implications for the financial market investors.

5. Robustness Analysis

In this section, we conduct further robustness analysis of our findings. *First*, we investigated the results within our overall data sample by using alternative division dates between the in-sample and out-of-sample periods in order to verify the performance of the proposed trading strategy when the proportions of data lengths are different between the in-sample period (i.e. the training period) and the out-of-sample period (i.e. the forecasting period in which the trading strategy is simulated). *Second*, we also attempted to evaluate the performance from the point of view of bull and bear market phases on the stock market. [9]

Our original in-sample period spans from 6th November 2009 to 24th May 2019 and the out–of–sample period starts on 25th May 2019 and ends on 15th February 2020

[9] We thank the anonymous Reviewers for these two suggestions, which prompted us to conduct more analyses, which we report in this section.

covering roughly 9 months. For the robustness analysis purposes, we adopted symmetrical division using +/- 4.5 months periods before and after the original division date, i.e. before and after 24th May 2019. Therefore, we distinguished the following alternative periods in order to verify the stability of our findings: shorter in-sample period and longer out–of–sample period (in-sample: 6th November 2009 - 11th January 2019 and out–of–sample: 12th January 2019 to 15th February 2020), which includes additional events between 12th January 2019 and 24th May 2019, and longer in-sample period and shorter out–of–sample period (in-sample: 6th November 2009 - 4th October 2019 and out–of–sample: 5th October 2019 - 15th February 2020).[10]

Table 8 presents the calculations for all the alternative periods and it shows that the patterns of results are very similar regardless of the choice of the division dates, which determined different proportions of data lengths across the in-sample period (i.e. the training period) and the out-of-sample period (i.e. the forecasting period). The strategy performs poorly until the end of day t and it consistently substantially improves in the remaining period until the end of day $t+1$. As Table 8 shows, for the whole trading horizon, the overall average returns until the end of day $t+1$ for the distinguished alternative division dates are always positive and also very similar numerically, i.e. they are: 0.07%, 0.09% and 0.06%, respectively.

Therefore, we can conclude that the choice of alternative division dates did not materially alter our findings, which are robust with respect to different divisions of the in-sample and out-of-sample periods.

[10] The estimation results of the dummy variables parameters from model (2) in the alternative in-sample periods are very similar and they do not differ much qualitatively. Moreover, even the numerical values of these estimates are often very close. For example, the estimate of the dummy variable for the current account announcements changes upwards in case of 10-years bond model in the original in-sample period ending on 24th May 2019 is -0.003910 (and it is significant at 10% level), while in the alternative in-sample period ending earlier on 11th January 2019 it is -0.003928 (and it is significant also at 10% level). Hence, we can test the proposed trading system in the alternative periods relying on the same decision rules as in the originally examined data samples.

Table 8. Results for alternative division dates between the in-sample period (i.e. the training period) and the out-of-sample period (i.e. the forecasting period)

Alternative out-of-sample periods	**Average profit / loss for trades after NBP announcement on day *t* at 2:00 p.m. CET for the trading horizon at the end of day *t***			
	10-years bond	5-years bond	WIG20 index	Overall average for all trades:
12th January 2019 to 15th February 2020	-0.04%	-0.02%	-0.03%	-0.03%
25th May 2019 – 15th February 2020	-0.05%	-0.03%	-0.03%	-0.04%
5th October 2019 – 15th February 2020	-0.14%	-0.01%	0.00%	-0.10%
Alternative out-of-sample periods	**Average profit / loss for trades after NBP announcement on day *t* at 2:00 p.m. CET for the trading horizon at the end of day *t+1***			
	10-years bond	5-years bond	WIG20 index	Overall average for all trades:
12th January 2019 to 15th February 2020	0.12%	0.05%	-0.32%	0.07%
25th May 2019 – 15th February 2020	0.16%	0.07%	-0.32%	0.09%
5th October 2019 – 15th February 2020	0.08%	0.02%	0.00%	0.06%

Notes: (1) Positions on days *t* and *t+1* are assumed to be closed at the end of the trading session at the Warsaw Stock Exchange, i.e. always at 5:00 p.m. CET time. (2) Cells highlighted in grey indicate positive average returns in respective alternative out-of-sample periods. (3) Overall averages for all trades in the last column are in most cases different than the simple averages across the traded instruments in the preceding columns due to different numbers of transactions for 10-years bond, 5-years bond and WIG20 index.

Next, we attempted to answer the question, relying also on the alternative out-of-sample periods distinguished above, whether the performance of the proposed trading strategy may differ in the bull market and bear market phases.

Although in the whole period from January 2019 until February 2020 the stock markets did not exhibit any clear bull market or bear market episodes, so such analysis was not possible to conduct to a full extent due to the nature of market data and the related data limitations, we could however investigate this issue indirectly by analysing the performance during the months when the main stock market index in Poland (i.e. the WIG index) recorded positive or negative returns, which can be treated as a proxy for either bull or bear market sentiment among the investors. The results of these calculations are reported in Table 9.

Overall, Table 9 shows a very clear tendency indicating that the performance of trades was better during the months characterized by positive stock market returns than during the months characterized by negative stock market returns. For the trading horizon until the end of day t, this pattern is visible in case of all variants of all three alternative out-of-sample investment horizons. For the trading horizon until the end of day $t+1$, such tendency appears to be the case in two out of three distinguished variants.

Therefore, it appears that the market sentiment does matter indeed for the strategy performance, although we could not conduct this investigation for clear bull market and clear bear market phases, because there were no such trends evident in the out-of-sample periods within our overall data sample, which we used in this study. Nevertheless, the results in Table 9 shed some light on this matter and they can open a new avenue for future investigations as the new data accumulates and when it permits such analyses to a fuller extent.

Table 9. Results for trades during months with positive and negative WIG stock index returns

Alternative out-of-sample periods	Average profit / loss for trades during months with positive and negative stock index returns after NBP announcement on day *t* at 2:00 p.m. CET for the trading horizon at the end of day *t*	
	Months with positive stock index returns:	**Months with negative stock index returns:**
12th January 2019 to 15th February 2020	0.01%	-0.04%
25th May 2019 – 15th February 2020	0.01%	-0.07%
5th October 2019 – 15th February 2020	-0.01%	-0.13%
Alternative out-of-sample periods	**Average profit / loss for trades during months with positive and negative stock index returns after NBP announcement on day *t* at 2:00 p.m. CET for the trading horizon at the end of day *t+1***	
	Months with positive stock index returns:	**Months with negative stock index returns:**
12th January 2019 to 15th February 2020	0.11%	0.05%
25th May 2019 – 15th February 2020	0.11%	0.07%
5th October 2019 – 15th February 2020	-0.06%	0.16%

Notes: (1) Cells highlighted in grey indicate better performance in respective alternative out-of-sample periods. (2) Months with positive and negative returns of the WIG index in Poland are as follows. Months with positive returns are: 01/2019, 04/2019, 06/2019, 09/2019, 10/2019 and 12/2019, while months with negative returns are: 02/2019, 03/2019, 05/2019, 07/2019, 08/2019, 11/2019, 01/2020 and 29/02/2020.

6. Discussion

The results from the first part of our analysis presented in this study are consistent with the findings from other markets (such as Bernanke and Kuttner (2005), Bekaert, Hoerova and Lo Duca (2013), Lucca and Moench (2015) and Cieslak, Morse and Vissing-Jorgensen (2020)), which also evidenced the statistically significant impact of monetary policy announcements released by central banks. Similarly to earlier papers using the data from Poland (see e.g. Brzeszczyński and Kutan (2015), Brzeszczyński et al. (2017) and Brzeszczyński et al. (2020)), we detected statistically significant reactions of the Polish financial market in all three analysed market segments: stock market, bonds market and foreign exchange market.

In the second part of our analysis, we explored the profit opportunities based on the statistically significant estimates of the NBP announcements binary dummy variables detected in the in–sample period, which we used as predictors for trades out–of–sample in the investment strategy based on the proposed trading rules. We found that for a number of different investment horizons, and for different levels of transaction costs, such profit opportunities did, indeed, exist.

Although only about 10% of the estimated parameters of the binary dummy variables capturing the NBP announcements were statistically significant in the initial regressions, they proved to be very profitable in the out–of–sample period.

At the end of day $t+1$, the individual trades delivered profits in 72.7% cases. The overall profitability across all events and all trading horizons was positive in as many as 63.6% cases.

Therefore, although the financial market in Poland was only moderately sensitive to the NBP communication, the identified types of central bank's announcements appear to be very useful for the investors, who can trade based on them and use them in the design of the fuzzy logic trading systems.

We also found that the NBP central bank's announcements affected the stock market faster than the bonds market. The reason for such pattern of reactions is most likely related to different levels of trading volume and the liquidity of bonds and stock market segments in Poland. For example, in 2019 the total turnover at the Warsaw Stock Exchange (WSE) on the main stock market was PLN 195,267 mln, whereas in the Catalyst market, which is one of the main Polish markets for trading bonds, in the same year 2019 the turnover was only PLN 2,743 mln (Rocznik Giełdowy (2020)). The total market value of stocks listed in on the WSE (domestic and foreign stocks jointly) was PLN 1,103.8 bn at the end of 2019, while the total value of treasury bonds' issues listed on the Catalyst bonds market in 2019 was 668.9 bn (Rocznik Giełdowy (2020)). Moreover, the number of active investors on the stock market is substantially higher too, which notably includes also many 'day traders' investor types, who operate on the stock market more intensively than on the bonds market. As a result, in 2019 the average number of transactions per one daily session on the WSE stock market was 72,125, whereas on the Catalyst bond market it was only 325, which confirms much lower activity of bonds market investors in Poland.

As Table 5 shows, the proposed trading strategy on the stock market produced (positive) returns faster, i.e. in shorter time horizon comparing with the bonds market. Also the magnitude of those changes is higher. These faster and stronger responses can be, therefore, related to different volumes of trade generated by much broader groups of market participants on the stock market, i.e. large number of individual investors along with institutional investors, whereas the bonds market is dominated only by institutional investors. In a broader perspective, higher trading volume is linked not only with higher liquidity, but also with higher market efficiency (Fama (1970) and

Fama (1991)). Therefore, lower market efficiency of bonds market (not only in Poland, but more generally in most other countries) can be treated as further explanation of different speeds of reaction of stock market and bonds market reported in our study.

Another important aspect of our findings, which should be mentioned here, is that even though the individual profits from such daily trades may look small, two practical things need to be emphasized: (1) The transactions in the proposed rule-based trading system are executed in very short time periods (lasting, effectively, only several hours), so they can be repeated multiple times as a substantially larger number of similar trades over a longer time period. Obviously, this kind of strategy can be also implemented in more than one market, so within one year, and in case of several markets, there may be easily more than 300 - 400 such transactions (which means on average 1-2 transactions per day) and (2) Such trades can also be executed using the financial leverage, which amplifies the generated profits (for example, trading on the WIG20 index signals using the WIG20 index futures automatically switches on the leverage with 20 multiple, which means that a seemingly small profit from one trade of e.g. just 0.25% is translated into the actual profit equal to 5%). Moreover, if the transactions are conducted through the spread betting platforms, the leverage for individual trades can be decided by the investors themselves, who can allocate it depending on, for example, the strength of the generated signals, which is the information that can also be extracted from such rule-based trading systems.

Hence, the performance of the proposed trading systems based on the fuzzy logic rules can be additionally enhanced in practice in order to achieve further improvement of the investment results, which opens up new avenues for future research.

7. Conclusions

In this paper, we proposed an investment strategy based on the trading rules to investigate the performance of investments on a broad financial market in Poland in its main three segments in response to central bank's communication of its monetary policy decisions.

The results of our analysis, relying on the application of the rule-based trading system, allowed to establish how much the central bank's announcements matter on a financial market. We designed a novel investment strategy and we simulated trades, which enabled us to quantify their profitability in the out–of–sample period using the data from a broad financial market in Poland spanning across 3 segments: stock market, foreign exchange market and bonds market.

Our results show evidence that the individual transactions delivered profits in 72.7% cases. The overall profitability across all events and all trading horizons was positive in as many as 63.6% cases.

In terms of the intra-daily patterns across days t and $t+1$, the results reported in this study show that the effects of the NBP monetary policy announcements manifest themselves most strongly on day $t+1$ with the best performance recorded on day $t+1$ by around 2:00 – 4:00 p.m. (but not at the very end of day $t+1$ at 5:00 p.m.).

Although the financial market in Poland was only moderately sensitive to the NBP central bank's communication, the identified types of the monetary policy announcements are helpful and economically significant for the investors, who can trade based on them and use such information in the design of the fuzzy logic trading systems.

Following the evidence from Poland reported in this study, further research using the data from other emerging and developed markets, relying on similar rule-based trading strategies, will enable international comparisons and it will help in establishing to what extent the results from this paper can be generalized also to other countries.

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