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This paper with the application of linear, nonlinear and long–run Granger causality tests, examines the causal links between the main Polish market price index (WIG) of the Warsaw Stock Exchange and four macroeconomic aggregates, namely the value of sold industrial production, the unemployment rate, the interest rate and the rate of inflation using monthly data for the period from January 1998 to June 2008. We found a bidirectional linear causal relationship between the stock market index and sold industrial production and strong evidence of linear and nonlinear Granger causality from changes in the interest rate to fluctuations in the stock market index. Furthermore, all examined macroeconomic variables were found to have a long-run causal influence on the performance of the stock market.

JEL-Classification: C32; G14

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1. Introduction

Since it was easy to observe a process of rapid development of Polish stock market, the research investigating causal links between stock market and the rest of economy has received considerable attention. The latter seems to be even more interesting if we look at the number of various financial sector reforms conducted in Poland in last two decades, the introduction of new economic instruments and the influence of globalisation on the structure of Polish economy. Altogether, the inner and outer factors had an important impact on the role that Polish stock market plays in economy.

The relationship between the stock market and the rest of the economy is important both for macroeconomists and finance specialists. Researchers may be interested in using this relationship in identifying and explaining some aspects of systemic risk. In the same time, market participants may regard the information about this relationship as a useful instrument for making decisions about their further investments. Thus, it seems worth to exploring the effect of certain fundamental macroeconomic news on stock market performance and vice versa.

Simultaneously, discussion about the set of macroeconomic variables which is suitable for examining the relationship with stock market performance is ongoing in various economies. There is a branch of previous studies concentrating on the influence of macroeconomic news on stock markets. Starting with the work of *Chen et al.*[1], the literature on Arbitrage Pricing Theory (APT) provided a framework for addressing the question of whether risk associated with macroeconomic variables is an important factor influencing stock returns. The impact of macroeconomic fundamentals on stock returns was the subject of research for *Fama*[2], *Balduzzi*[3], *Graham*[4] and *Fama* and *Schwert*[5]. All these authors found a unidirectional influence of the examined economic variables on stock markets.

The investigation of a relationship in the opposite direction (from stock market to macroeconomic variables) was the subject of many publications too. At this point let us just mention *Tobin's*[6] fundamental paper or more recent results presented by *Morck et al.*[7],

1 Cf. *Chen/Roll/Ross* (1986).
2 Cf. *Fama* (1981).
3 Cf. *Balduzzi* (1995).
4 Cf. *Graham* (1996).
5 Cf. *Fama/Schwert* (1997).
6 Cf. *Tobin* (1969).
7 Cf. *Morck/Schleifer/Vishny* (1990).

Blanchard et al.[8], and *Chirinko* and *Schaller*[9]. The main problem discussed in this literature is whether or not investors should regard the stock market as a helpful tool in making real decisions.

In this paper apart from the market price index (WIG) of the Warsaw Stock Exchange (WSE) we consider a set of monthly macroeconomic aggregates containing the value of sold industrial production, interest rates, inflation rates and the rate of unemployment in Poland in the period from January 1998 to June 2008. In order to investigate the dynamic relationships between the examined variables we use the definition of causality formulated by *Granger*[10]. The first version of the Granger test was based on asymptotic distribution theory. However, this approach could lead to spurious results if the considered time series were nonstationary[11]. As a cure for this problem the ideas of a cointegration and vector error correction model (VECM) were developed by *Granger*[12]. Here we must note that there are also some papers[13] supporting the hypothesis that asymptotic distribution theory is an improper tool for testing the causality of integrated variables by means of the VAR model. This idea leads to another concept of causality testing which is based on a Wald test statistic.

The subject of nonlinear causality tests has been raised many times in recent years[14]. This increasing interest in nonlinear techniques is justified by empirical studies which demonstrate that traditional linear tests may have low power in detecting some kinds of nonlinear dependences. The starting point for investigations concentrated on nonlinear causal dependences was related to a nonparametric statistical method presented by *Baek* and *Brock*[15]. Some further modifications of this approach were made by *Hiemstra* and *Jones*[16]. Their concept improved the small-sample properties of the test and relaxed the assumption that the series to which the test was applied were i.i.d. Another modification of the method was proposed by *Diks* and *Panchenko*[17]. The authors uncovered and solved the problem of the null hypothesis in the HJ (*Hiemstra* and *Jones*) test which generally was not equivalent to Granger noncausality. Furthermore, *Diks* and *Panchenko* found their test to have better

8 Cf. *Blanchard/Changyong/Summers* (1993).
9 Cf. *Chirinko/Schaller* (1996).
10 Cf. *Granger* (1969).
11 Empirical findings – cf. *Granger/Newbold* (1974); theoretical explanation – cf. *Phillips* (1986).
12 Cf. *Granger* (1988).
13 Cf. *Sims/Stock/Watson* (1990); *Toda/Yamamoto* (1995).
14 Cf. *Abhyankar* (1998); *Asimakopoulos/Ayling/Mahmood* (2000).
15 Cf. *Baek/Brock* (1992).
16 Cf. *Hiemstra/Jones* (1994).
17 Cf. *Diks/Panchenko* (2005); *Diks/Panchenko* (2006).

performance than the HJ one, especially in terms of over-rejection and size distortion, which are quite often reported for the HJ test.

The main goal of this paper is to analyze the causal relationships between the considered variables in terms of both linear and nonlinear short-term Granger causality as well as long-term relations. Another issue worth investigating is the connection between causality and market efficiency. According to the Efficient Market Hypothesis (EMH) all the market participants have perfect knowledge of all information available in market at a specific moment. Thus, stock prices reflect all past and current seminal information, including macroeconomic data. This assumption leads to a situation where investors are not able to earn systematically higher than a normal return, since any useful trading rule cannot exist. Furthermore, there is a simple relationship between market efficiency and Granger causality. Namely, if there is no unidirectional lagged causal relationship from a macroeconomic variable to stock prices then informational efficiency of the considered market may exist. On the other hand, the market is informationally inefficient if there exists a causal link from some macroeconomic aggregates to stock market. Furthermore, finding causality in the direction from lagged values of the stock prices to some macroeconomic variable does not violate informational efficiency assumption.

With the application of all the above methods we tend to draw a net of connections between the financial sector and the real economy in Poland in the time period under study. We are interested in selecting a set of those macroeconomic fundamentals which have the strongest dynamic link with the performance of the WSE.

2. Dataset overview

In order to perform our analysis we use a dataset containing essential information. Our research is based on monthly data from January 1998 to June 2008 for all considered variables of the model, namely the market price index (WIG) of the Warsaw Stock Exchange, the unemployment rate in Poland, the value of sold industrial production, the interest rate (reference) in Poland and the rate of inflation. As a measure of the performance of the real economy we use the value of sold industrial production rather than gross domestic product, since monthly data was available for industrial production and only quarterly data was available for GDP. The full sample contains 126 observations. The data describing market price index of the Warsaw Stock Exchange was gained from PARKIET.

Other data was obtained from the Statistical Office in Cracow. In this paper we use abbreviations for all the examined variables. Table 1 contains suitable information.

Full name of considered variable	**Shortcut name**
Market price index of Warsaw Stock Exchange	WSE
Unemployment rate in Poland	UNEMPL
Sold industrial production in Poland[18]	PROD
Inflation rate in Poland	INFL
Interest rate (reference) in Poland	IRT

Table 1: Abbreviations for examined variables

In the further calculations we use a natural logarithm of WSE and PROD variables. It should be mentioned that the use of a natural logarithm improves some of the statistical properties of the financial time series distribution (especially in terms of normality, which is a prior condition for standard statistical techniques). Furthermore, since the logarithmic transformation belongs to the Box–Cox transformation, it can stabilize the variance. Table 2 contains descriptive statistics of all the examined variables.

Statistic \ Variable	**ln(WSE)**	**UNEMPL (in %)**	**IRT (in %)**	**ln(PROD)**	**INFL (in %)**
Minimum	9.33	9.40	4.00	10.24	0.30
1st Quartile	9.62	12.10	5.25	10.53	1.60
Median	9.89	15.90	6.50	10.66	3.60
3rd Quartile	10.41	19.27	15.50	10.96	6.82
Maximum	11.09	20.70	24.00	11.27	14.20
Mean	10.03	15.59	9.99	10.73	4.64
Standard deviation	0.50	3.57	6.05	0.28	3.77
Skewness	0.68	–0.20	0.73	0.17	0.87
Kurtosis	–0.88	–1.34	–0.85	–1.11	–0.33

Table 2: Descriptive statistics of considered variables

Directly from this table we can notice some interesting information. The inflation rate, interest rate and the rate of unemployment vary significantly in the period under study, as we

18 It is expressed in mln PLN.

analyze the range and standard variation of mentioned variables. This may somehow be interpreted as an effect of the whole gamut of changes in the financial structure of Polish economy, which have taken place in recent years.

3. Long- and short-term Granger causality

To explore the dynamic short-run relations between the considered variables we use both linear and nonlinear Granger causality tests. As already mentioned our main goal was to investigate which macroeconomic fundamentals have the strongest influence on WSE performance in terms of Granger causality.

In this paper we use the definition of causality formulated by *Granger*[19]. To explain the idea of this causality let $\{X_t\}$ and $\{Y_t\}$ denote two scalar-valued, stationary and ergodic time series. Furthermore, let $F\{X_t \mid I_{t-1}\}$ stand for the conditional probability distribution of X_t, given the bivariate information set I_{t-1}. The mentioned set I_{t-1} contains L_X – lagged vector of X_t ($X_{t-L_X}^{L_X} := (X_{t-L_X}, X_{t-L_X+1}, ..., X_{t-1})$) and L_Y – lagged vector of Y_t ($Y_{t-L_Y}^{L_Y} := (Y_{t-L_Y}, Y_{t-L_Y+1}, ..., Y_{t-1})$). After choosing numbers of lags L_X and L_Y, we say that the time series $\{Y_t\}$ does not strictly cause the time series $\{X_t\}$, if:

$$F(X_t \mid I_{t-1}) = F(X_t \mid I_{t-1}^*),\ t = 1,2...,\ (1)$$

where I_{t-1}^* stands for an information set including lagged values of X_t only. This definition may also be formulated in a different way, namely, if the knowledge of past values of time series $\{Y_t\}$ improves the short-run prediction of current and future values of $\{X_t\}$, then equality (1) does not hold and $\{Y_t\}$ is said to strictly Granger cause $\{X_t\}$.

One of the most important issues related to conducting linear Granger causality tests is operating on stationary time series. Testing for this type of causality may lead to spurious results if the analyzed time series are indeed nonstationary. This problem was described by Granger based on a series of relevant simulations. The theoretical explanation of the spurious relations observed while testing for linear Granger causality in the case of nonstationary time series was the subject of *Phillips'* publication[20]. The mentioned problems

19 Cf. *Granger* (1969).
20 Cf. *Phillips* (1986).

force the researcher to conduct precisely all the tests of stationarity and in the case of nonstationarity, additionally establish the order of integration[21].

Therefore, our initial analysis should start with some tests of stationarity. We applied one of the most common statistical instruments which is helpful in establishing the order of integration of an examined time series – the augmented Dickey-Fuller unit root test. This test is based on the following regression model:

$$\Delta w_t = a + b w_{t-1} + \sum_{i=1}^{m} c_i \Delta w_{t-i} + u_t \,, \qquad (2)$$

where $\{w_t\}$ denotes the time series being analyzed, m stands for the lag length, Δ denotes the differencing operator and u_t is assumed to be white noise. The time series $\{w_t\}$ is nonstationary if the null hypothesis (described by the condition $b = 0$) can not be rejected at a fixed significance level. The one-sided alternative is described by the formula $b < 0$ and it corresponds to the stationarity of the analyzed time series. For the critical values we refer to *Charemza* and *Deadman*[22]. Tables 3–4 contain the results of all the conducted tests of stationarity. In order to choose the optimal lag length (*m*) we set up the maximal lag length equal to 10 and then we used AIC and BIC information criteria to choose *m* from the set {0, 1,…, 10}.

Variable	**Optimal lag length**	**Test Statistics**	**Critical value**		
			10%	**5%**	**1%**
ln(WSE)	1	**1.00**	–1.62	–1.94	–2.56
UNEMPL	5	**–0.30**			
ln(PROD)	6	**3.07**			
INFL	1	**–1.53**			
IRT	6	**–1.27**			

Table 3: The results of tests of stationarity of considered variables (levels)

Variable	**Optimal lag length**	**Test Statistics**	**Critical value**		
			10%	**5%**	**1%**
Δln(WSE)	4	**–4.09**	–1.62	–1.94	–2.56
ΔUNEMPL	0	**–5.74**			
Δln(PROD)	6	**–3.39**			
ΔINFL	0	**–3.01**			
ΔIRT	5	**–2.90**			

Table 4: The results of tests of stationarity of considered variables (first differences)

21 Order of integration of time series $\{w_t\}$ is the smallest natural number *k*, for which $\Delta^k w_t$ is a stationary time series. Differencing leads to reduction (removal) of deterministic trend only.
22 Cf. *Charemza/Deadman* (1997).

As we can see for the levels of all the examined time series the ADF test accepts the null hypothesis at typical significance levels (see table 3). After taking first differences, the results strongly point at stationarity (the null hypothesis is rejected), thus all time series are integrated in the first order (see table 4).

As was shown by Granger, while conducting causality tests for nonstationary time series integrated in the same order, the application of a standard VAR model (certainly constructed for appropriately differenced variables) may lead to spurious conclusions. These circumstances may occur when time series are cointegrated[23]. In this case the standard VAR model must be expanded with an appropriate error correction mechanism[24]. Therefore, the next part of this article contains cointegration analysis.

To examine the problem of cointegration we applied some typical tests. For each conducted test we had to set up a proper lag length (otherwise spurious results may occur). To choose the optimal lag length we used AIC, BIC and FPE information criteria (once again we set up the maximal lag length at the level of 10). To determine the number of cointegrating relations, we proceed sequentially from r=0 to r=4 until we fail to reject (r denotes examined number of cointegrating vectors). The results of cointegration analysis are shown in table 5:

Johansen trace test			**Maximal eigenvalue test**			**Saikkonen-Lutkepohl Test**		
H_0	H_1	p-value	H_0	H_1	p-value	H_0	H_1	p-value
r=0	r>0	0.0013	r=0	r=1	0.0040	r=0	r>0	$<10^{-4}$
r<=1	r>=2	0.0969	r=1	r=2	0.1183	r=1	r>1	0.0693
r<=2	**r>=3**	**0.4281**	**r=2**	**r=3**	**0.5935**	**r=2**	**r>2**	**0.6680**
r<=3	r>=4	0.4277	r=3	r=4	0.6154	r=3	r>3	0.5889
r<=4	r=5	0.1212	r=4	r=5	0.1212	r=4	r=5	0.7401
Optimal lag length: 4			Optimal lag length: 4			Optimal lag length: 3		

Table 5: Cointegration analysis

The further research is based on establishing the proper number of cointegrating vectors. Basing on results presented in table 5 we decided to establish the number of cointegrating vectors at the level of two (insufficient support (at 10% significance level) for hypothesis that r=1)[25]. To complete the construction of our VECM we must once again establish an

23 Cointegration is the property of nonstationary time series integrated in the same order, which causes the existence of such a linear combination of these series, which is stationary or "less nonstationary" than each of component series.
24 These are Vector Error Correction Models (VECM).
25 Additionally, the results presented in table 5 confirmed that considered time series are indeed nonstationary. Namely (see the next to last row of table 5), they provided no basis (at 10% significance level) for claiming that r=5. It is a well known fact that the case of full rank (r=5) refers to stationarity of all considered time series.

appropriate lag length with the help of information criteria (analogously to former cases). After setting this number at the order of 3, we get a model of the form:

$$U_t = c + \sum_{i=1}^{3} \alpha_i U_{t-i} + \beta_1 EC_{1,t-1} + \beta_2 EC_{2,t-1} + \varepsilon_t, \quad t = 5,...,126, \qquad (3)$$

where $U_t = \left[\Delta \ln(WSE_t), \Delta UNEMPL_t, \Delta \ln(PROD_t), \Delta INFL_t, \Delta IRT_t\right]^T$, c, β_1, β_2 are 5×1 vectors of parameters, α_i are 5×5 matrices of parameters for i=1,2,3 and ε_t are 5×1 vectors of residuals. The results of further estimation lead to an error correction mechanism which is expressed by following formulas:

$$EC_{1,t} = INFL_t + 1{,}11 IRT_t - 18{,}67 \ln(WSE_t) + 53{,}34 \ln(PROD_t) \qquad (4)$$

$$EC_{2,t} = UNEMPL_t - 0{,}96 IRT_t + 30{,}6 \ln(WSE_t) - 58{,}43 \ln(PROD_t) \quad (5).$$

Let us now give a short briefing on the linear causality tests conducted for the use of this paper. In the beginning we must underline one important fact. As was shown by *Lütkepohl*[26], the process of separate estimation of equations (3) leads to an identical and unbiased appraisal of parameters as it is in the case of joint estimation[27]. Thus, to test for linear Granger causality we use a vector error correction model (VECM) for two variables, which may be presented in the following form (we present the example of $\Delta \ln(WSE_t)$ and $\Delta \ln(PROD_t)$ variables, models for other pairs of variables will be analogous):

$$\begin{cases} \Delta\ln(WSE_t) = c_1 + \sum_{i=1}^{3}\left[\alpha_{i11}\Delta\ln(WSE_{t-i}) + \alpha_{i12}\Delta UNEMPL_{t-i} + \alpha_{i13}\Delta\ln(PROD_{t-i}) + \alpha_{i14}\Delta INFL_{t-i} + \alpha_{i15}\Delta IRT_{t-i}\right] + \beta_{11}EC_{1,t-1} + \beta_{21}EC_{2,t-1} + \varepsilon_{1t} \\ \Delta\ln(PROD_t) = c_3 + \sum_{i=1}^{3}\left[\alpha_{i31}\Delta\ln(WSE_{t-i}) + \alpha_{i32}\Delta UNEMPL_{t-i} + \alpha_{i33}\Delta\ln(PROD_{t-i}) + \alpha_{i34}\Delta INFL_{t-i} + \alpha_{i35}\Delta IRT_{t-i}\right] + \beta_{13}EC_{1,t-1} + \beta_{23}EC_{2,t-1} + \varepsilon_{3t} \end{cases} \qquad (6)$$

where vectors $c = \left[c_k\right]_{5\times 1}, \beta_1 = \left[\beta_{1k}\right]_{5\times 1}, \beta_2 = \left[\beta_{2k}\right]_{5\times 1}, \varepsilon_t = \left[\varepsilon_{kt}\right]_{5\times 1}$ and matrices $\alpha_i = \left[\alpha_{ijk}\right]_{5\times 5}$ are the same as in the case of equation (3).

To test for short-run linear Granger causality we used the simple *F* test. If the null hypothesis $\alpha_{i13} = 0$ ($\alpha_{i31} = 0$) for $i = 1,2,3$ is rejected at a sensible significance level, then we may say that $\Delta \ln(PROD)$ Granger causes $\Delta \ln(WSE)$ ($\Delta \ln(WSE)$ Granger causes $\Delta \ln(PROD)$).

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26 Cf. *Lütkepohl* (1991).
27 The considered estimation method is ordinary least squares (OLS) method.

At this place we must underline some important facts. Firstly, parametric tests (like *F* test) require some specific modelling assumptions (for example homoscedastic error term). If these assumptions do not hold then the test results may be spurious. Secondly, tests based on prediction errors are sensitive only to causality in mean (causality in higher-order structure can not be explored). Therefore, in this article besides the traditional linear Granger causality tests we use their nonlinear equivalent too. As we mentioned in the introductory paragraph, in recent years the test proposed by *Baek* and *Brock* has been modified several time. Our approach is based on modifications proposed by *Diks* and *Panchenko*. This nonparametric method reduces possible problems resulting from model misspecification and performs relatively well also in cases of untypical heteroscedastic structures[28].

To understand the idea of nonlinear causality tests let us focus on the problem of investigating whether time series $\{X_t\}$ Granger causes time series $\{Y_t\}$ (testing for causality in the opposite direction requires analogous analysis). Let us now define for *t*=1, 2… the $L_X + L_Y + 1-$dimensional vector $W_t := (X_{t-L_X}^{L_X}, Y_{t-L_Y}^{L_Y}, Y_t)$. Using the terminology of density functions we may write the null hypothesis that $\{X_t\}$ does not Granger cause $\{Y_t\}$ in the following form:

$$\begin{aligned} f_{X,Y,Z}(x,y,z) &= f_{X,Y}(x,y) f_{Z|X,Y}(z \mid x,y) = \\ &= f_{X,Y}(x,y) f_{Z|Y}(z \mid y) \end{aligned} \quad , \qquad (7)$$

where $f_W(x)$ denotes the probability density function of random vector *W* at point *x*, $X = X_{t-L_X}^{L_X}$, $Y = Y_{t-L_Y}^{L_Y}$, $Z = Y_t$ for $t = 1,2,...,$ with the meaning of other symbols already explained in this article (compare the definition of causality contained in this paper). We may also present the last equation in more convenient forms:

$$\frac{f_{X,Y,Z}(x,y,z)}{f_{X,Y}(x,y)} = \frac{f_{Y,Z}(y,z)}{f_Y(y)} \qquad (8)$$

and

$$\frac{f_{X,Y,Z}(x,y,z)}{f_Y(y)} = \frac{f_{X,Y}(x,y)}{f_Y(y)} \frac{f_{Y,Z}(y,z)}{f_Y(y)} \qquad (9).$$

28 Cf. *Diks/Panchenko* (2006).

The following expression defines the correlation integral $C_W(\varepsilon)$ (symbol W stands for multivariate random vector):

$$C_W(\varepsilon) = P\left(\|W_1 - W_2\| \le \varepsilon\right) = \iint I(\|s_1 - s_2\| \le \varepsilon) f_W(s_1) f_W(s_2) ds_2 ds_1 , \qquad (10)$$

symbols W_1, W_2 denote independent multivariate random vectors with distributions in the equivalence class of distribution of vector W, letter I stands for the indicator function (equal to one if the condition in brackets holds true, otherwise equal to zero), $\|x\| = \sup\{|x_i| : i = 1,...,d_W\}$ denotes the supremum norm (d_W is the dimension of sample space W) and $\varepsilon > 0$.

According to *Hiemstra* and *Jones*, testing the null hypothesis in Granger's causality tests implies for every $\varepsilon > 0$:

$$\frac{C_{X,Y,Z}(\varepsilon)}{C_{X,Y}(\varepsilon)} = \frac{C_{Y,Z}(\varepsilon)}{C_Y(\varepsilon)} \qquad (11)$$

or equivalently:

$$\frac{C_{X,Y,Z}(\varepsilon)}{C_Y(\varepsilon)} = \frac{C_{X,Y}(\varepsilon)}{C_Y(\varepsilon)} \frac{C_{Y,Z}(\varepsilon)}{C_Y(\varepsilon)} \qquad (12).$$

Their further approach to causality testing is based on calculating sample versions of correlation integrals and then testing whether left-hand- and right-hand-side ratios differ significantly or not. They propose the application of the following formula as correlation integral estimator:

$$C_{W,n}(\varepsilon) = \frac{2}{n(n-1)} \sum\sum_{i<j} I_{ij}^W \qquad (13),$$

where $I_{ij}^W = I(\|W_i - W_j\| < \varepsilon)$. *Diks* and *Panchenko*[29] showed that testing relations (11) or (12) is not equivalent, in general, to testing the null hypothesis of Granger causality. Their achievement without doubt (2006) is finding exact conditions under which a HJ test is useful

29 Cf. *Diks/Panchenko* (2005).

in investigations concentrated on causality. This fact is not the main point of our research, thus we refer to *Diks* and *Panchenko*[30] for more details on this issue.

For the use of this paper we apply the *Diks* and *Panchenko* modification of *Hiemstra* and *Jones* test of nonlinear Granger causality. In terms of expected value and density functions *Diks* and *Panchenko* managed to bypass the above mentioned problem of testing for an incorrect hypothesis. They also showed the asymptotical theory of the modified test statistic. Furthermore, with the help of numerical simulations performed for relatively long time series they presented some advice concerning the proper way of choosing the bandwidth depending on sample size. They claimed that this adaptation may be helpful in reducing the bias of the test, which is one of the serious problems that arise for long time series.

Since former studies brought no clear suggestions about the appropriate way of choosing the bandwidth parameter in the case of relatively small samples, we have decided to set up its value at the level of one (ε=1) in the case of all the conducted tests[31]. We have also decided to use the same lags for every pair of time series being analyzed ($L_X = L_Y$), establishing this lag at the order of 1, 2 and 4.

We performed our calculations on the basis of residual time series resulting from the appropriate VEC model. The application of residual time series is justified by the fact that they reflect strict nonlinear dependencies (the linear causality had been examined by VECM and traditional linear methods). The time series of residuals are both standardized, thus they share a common scale parameter.

Let us finally throw some light on the issue of the long-run causality tests used in this paper. The idea of this type of causality analysis is based on the existence of a cointegrating relation between the analyzed variables[32]. To better understand this issue consider a bivariate VECM (with one cointegrating vector) of the following form:

$$\begin{cases} \Delta y_t = \mu_y + \sum_{j=1}^{k} \alpha_{0,j} \Delta y_{t-j} + \sum_{j=1}^{k} \beta_{0,j} \Delta x_{t-j} + A(y_{t-1} + \alpha x_{t-1}) + \varepsilon_t \\ \Delta x_t = \mu_x + \sum_{j=1}^{k} \alpha_{1,j} \Delta x_{t-j} + \sum_{j=1}^{k} \beta_{1,j} \Delta y_{t-j} + B(y_{t-1} + \alpha x_{t-1}) + \varepsilon_t^{'} \end{cases}, \quad (14)$$

30 Cf. *Diks/Panchenko* (2006).

31 This value was commonly used in former studies (see e.g. *Hiemstra/Jones* (1994), *Diks/Panchenko* (2005, 2006))

32 Cf. *Cheng/Taylor/Weng* (2006).

where $\{x_t\}$, $\{y_t\}$ are analyzed time series, $\{\varepsilon_t\}$ and $\{\varepsilon'_t\}$ denote residual series and $EC_{t-1} = y_{t-1} + \alpha x_{t-1}$ is the cointegrating equation. According to *Granger*[33], if $\{x_t\}$, $\{y_t\}$ are indeed cointegrated, this is a sufficient condition for the existence of long-run Granger causality in at least one direction. To justify this fact let us assume that cointegration between $\{x_t\}$, $\{y_t\}$ is statistically significant, which of course implies $|A| + |B| > 0$. Assumption of the condition $A \neq 0$ in equations (14) is sufficient to establish Granger causality from $\{x_t\}$ to $\{y_t\}$, because changes in EC_{t-1} cause changes in y_t. If we imagine a situation when $EC_{t-1} = 0$ then a change in x_t without a contemporaneous change in y_t cause disequilibrium. The system returns to equilibrium as the assumption $A \neq 0$ causes subsequent changes in $\{y_t\}$. As we can see changes in the $\{x_t\}$ time series precede changes in the $\{y_t\}$ time series, which clearly implies Granger causality. Analogous reasoning leads to the conclusion that $\{y_t\}$ Granger causes $\{x_t\}$, if we assume that $B \neq 0$.

We must remember that even if both parameters *A* and *B* are statistically insignificant it does not exclude the possibility of the existence of short-run Granger causality. This situation only forces the researcher to continue some further investigations, like testing the statistical significance of other parameters in equations (14) (see the description of linear causality tests contained in this paper) or performing some nonlinear tests.

The model constructed for the use of this article contains five equations, thus the mentioned idea of testing for long-run causal effects must be modified. Namely, to establish a Granger causality (in this case based on cointegration equations) from variable *X* to variable *Y* we consider an appropriate equation (with *Y* on left side) and then test whether the linear combination of *EC*'s on the right side of the examined equation contains a statistically significant coefficient associated with the variable *X*. Finally, we must note that if $\{x_t\}$ and $\{y_t\}$ are cointegrated and generated by suitable VAR model then according to Granger representation theorem error term in model (14) is a white noise and therefore the results of standard significance test stay valid. Otherwise (model misspecification) standard *t*-test may lead to spurious results and some other statistic methods should be applied to test for causality.

33 Cf. *Granger* (1969).

4. Empirical results

In this paragraph we present the results of both linear and nonlinear short-run causality tests, as well as the outcomes of long-run Granger causality analysis. These findings bring some essential data which are helpful in describing the dynamic relationships between the WIG Index and some key macroeconomic fundamentals of Poland in the period under study. Because traditional linear Granger causality tests tend to have low power in detecting some kinds of nonlinear dependences[34], we extended our research by the application of nonlinear tests and cointegration causality analysis.

The table above illustrates the *p*-values obtained from testing for linear Granger causality in the case of the examined VEC model. The considered null hypothesis refers to a situation when variable *X* does not Granger cause variable *Y*. The bold face refers to results supporting the hypothesis of the existence of linear Granger causality in the considered direction at a 10% significance level.

X \ *Y*	**Δln(WSE)**	**Δln(PROD)**	**ΔUNEMPL**	**ΔINFL**	**ΔIRT**
Δln(WSE)		**0.08**	**0.04**	0.46	0.33
Δln(PROD)	**0.10**		**0.002**	0.12	0.38
ΔUNEMPL	0.53	**0.0005**		0.49	0.16
ΔINFL	0.55	0.82	0.91		**0.004**
ΔIRT	**0.09**	0.94	**0.02**	**0.05**	

Table 6: The results of linear Granger causality tests

As we can see the conducted tests strongly support the hypothesis about bidirectional causality between Δln(WSE) and Δln(PROD). On the other hand the test results provide no evidence of Granger causality in the direction from ΔUNEMPL to Δln(WSE) and from ΔINFL to Δ ln(WSE). Finally, we must note that changes in interest rate Granger cause Δln(WSE) variable.

A bidirectional causal relationship was found between ΔUNEMPL and Δln(PROD) variables. It is worth underlining the fact that the *p*-values obtained for this pair of variables reached values extremely close to zero, which seems to be even stronger evidence of causality.

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34 Cf. *Brock* (1991).

The analysis of the relations between ΔIRT and other variables indicates that the test results supply evidence of a causal relationship in the direction from changes in the interest rate to variations in the unemployment rate. Finally, our findings indicate a bidirectional causal relationship between the ΔIRT and ΔINFL variables.

Let us now move to a presentation of the results of the nonlinear causality test results conducted for the residual series derived from our VEC model. Once again the considered null hypothesis refers to a situation when variable *X* does not Granger cause variable *Y*. The bold face indicates analogous cases as in table 6. As we have already mentioned all tests were conducted with a bandwidth parameter equal to one (ε=1).

X \ *Y*	**Δln(WSE)**	**Δln(PROD)**	**ΔUNEMPL**	**ΔINFL**	**ΔIRT**	**Lag length**
Δln(WSE)		0.19	0.13	0.38	0.26	1
		0.33	0.20	0.28	0.49	2
		0.39	0.40	0.35	0.40	4
Δln(PROD)	0.27		0.66	0.71	0.65	1
	0.79		0.14	0.56	0.24	2
	0.63		**0.05**	0.31	0.31	4
ΔUNEMPL	0.15	0.35		0.24	0.59	1
	0.25	**0.03**		**0.06**	0.37	2
	0.31	0.21		**0.10**	0.24	4
ΔINFL	0.71	0.35	0.41		0.25	1
	0.44	0.42	0.45		**0.07**	2
	0.73	0.26	0.42		**0.03**	4
ΔIRT	**0.02**	0.25	0.24	0.15		1
	0.16	0.17	0.23	**0.08**		2
	0.23	0.35	**0.09**	0.41		4

Table 7: The results of nonlinear causality tests

This time the test results indicate the existence of unidirectional nonlinear causal relationship from ΔIRT to Δln(WSE) as well as from ΔIRT to ΔUNEMPL. The bidirectional relationship between ΔUNEMPL and Δln(PROD) variables was found once again, which may be an evidence of extremely strong causal relationship between examined pair of variables (both linear and nonlinear causality was established).

Furthermore, after analyzing table 7, one can easily find that the conducted tests provide a strong basis for claiming that there exists a bidirectional nonlinear causal relationship between ΔIRT and ΔINFL variables. Once again this relationship seems to be enormously strong, if we look at similar results gained with the application of linear test.

As we have already mentioned traditional linear Granger causality test tend to have low power in detecting some kinds of nonlinear relationships. If we compare test results for pair ΔUNEMPL and ΔINFL presented in tables 6-7 we will easily see that traditional linear test provided basis to claim that there is no causality in any direction. However, the results of nonlinear test strongly support hypothesis of unidirectional causality in the direction from ΔUNEMPL to ΔINFL.

In order to perform long-run causality analysis we conducted series of tests for exclusion of insignificant variables. Namely, we performed sequential elimination which at each step omits the variable with the highest *p*-value, until all remaining variables have a *p*-value no greater than 0.05. We had omitted (replaced) all insignificant variables, since this re-estimation was applied for each equation separately.

Let us now move to the presentation of results of cointegration causality tests conducted for our restricted VEC model. The following table contains suitable outcomes. Once again the considered null hypothesis refers to situation when variable *X* does not Granger cause variable *Y*. The test results are presented in the form:

Result
(*p*-value of EC_1 component; *p*-value of EC_2 component)

where variable "Result" is "YES", if at least one of cointegration components was statistically significant at 5% significance level (and certainly included a cause variable), or "NO" otherwise. Once again we used the bold face to make presentation of our results more transparent.

X \ *Y*	**Δln(WSE)**	**Δ ln(PROD)**	**ΔUNEMPL**	**ΔINFL**	**ΔIRT**
Δln(WSE)		**YES** (**0.001** ; >0.05)	**YES** (>0.05 ; **<10^{-6}**)	**YES** (**0.01** ; >0.05)	NO (>0.05 ; >0.05)
Δ ln(PROD)	**YES** **(0.003;0.002)**		**YES** (>0.05 ; **<10^{-6}**)	**YES** (**0.01** ; >0.05)	NO (>0.05 ; >0.05)
ΔUNEMPL	**YES** **(0.003;0.002)**	NO (>0.05 ; >0.05)		NO (>0.05 ; >0.05)	NO (>0.05 ; >0.05)
ΔINFL	**YES** **(0.003;0.002)**	**YES** (**0.001** ; >0.05)	NO (>0.05 ; >0.05)		NO (>0.05 ; >0.05)
ΔIRT	**YES** **(0.003;0.002)**	**YES** (**0.001** ; >0.05)	**YES** (>0.05 ; **<10^{-6}**)	**YES** (**0.01** ; >0.05)	

Table 8: Long-run (cointegration) causality analysis

One can easily see that these outcomes lead to many interesting observations. Let us underline the fact that all considered macroeconomic fundamentals turned out to Granger cause the changes of natural logarithm of WSE variable. Another result worth mentioning is the fact that the changes of interest rate were found to be the cause for all other examined variables. Furthermore, in this case no feedback relation was found.

It also should be noted that Δln(WSE) was found to be the cause of all examined variables except ΔIRT (which means bidirectional causality in all except one case). Finally, one must note that our research provided evidence of bidirectional causality between ΔINFL and Δln(PROD) and unidirectional causality from Δln(PROD) to ΔUNEMPL.

5. Concluding remarks

The objective of this paper was to examine the joint dynamics of the market price index of the Warsaw Stock Exchange and chosen macroeconomic variables, namely the value of sold industrial production, the interest rate, the inflation rate and the rate of unemployment in Poland. Our investigation was based on monthly data and covered the period from January 1998 to June 2008. In order to test for short-run Granger causality we used both linear and nonlinear methods. Additionally, we extended our research by the application of cointegration (long-run) causality tests.

The results of the linear causality analysis strongly support the hypothesis that the Polish stock market is informationally inefficient with respect to the value of sold industrial production and the interest rate. On the other hand, the test results provided grounds for claiming that the stock market has already incorporated all past information on the unemployment and inflation rates, as there was no linear causal influence found in these cases.

In the past, the behavior of the Warsaw Stock Exchange index indicated a few times in short term the upcoming economic growth decline of Polish economy (and the resulting rise of unemployment). There was the case in 1998 after Russian crisis, when the fall at WSE market index caused slowing down of GDP growth and rising unemployment rate in two months. Also in the time period 2000-01, after Internet market boom, drop (rise) at WSE market index ‘predicted’ beginning of slowdown (growth) of Polish GDP and increment (decrease) of unemployment rate. The reasons for the fall at WSE market index in 2008 were not fundamentals of Polish economy (they were good) but speculations on international financial and capital markets, especially impact of situation on Wall Street at Polish stock market. Probably for this reason no significant changes of unemployment or inflation rate in Polish economy as effect of declining WSE market index has been noticed for this year.

It results from the economic theory that e.g. changes in stock index should have impact on changes in unemployment rate and vice versa. Linear causality test detects in our dataset as a whole a causal unidirectional relation (from stock index to unemployment), while nonlinear does not. Cointegration analysis led us (in line with linear causality test) to establishment of unidirectional long-run causality from changes of the stock market index to changes of the unemployment. Uncertainty of tests results concerning actual causality between these variables may be caused by the fact that in considered time period of more than ten years monthly data must be applied (because lack of more detailed data for industrial production in Poland) and some possible weak intermediate dependencies (causalities) might overlap and/or statistically cancel out.

The application of the nonlinear Granger causality tests also led us to some important conclusions. Firstly, let us note that our research once again confirmed that a linear Granger causality tests may often be an inappropriate tool for performing investigations of the causal dependences in the case of nonlinear relationships. This effect was presented using the example of outcomes for the ΔUNEMPL and ΔINFL variables. Secondly, one must note that for some pairs of examined variables the results of the nonlinear Granger causality test confirmed the existence of a causal relationship, which had previously been indicated by a linear test. This may be interpreted as proof of extremely strong causal links. Therefore, the evidence of the informational inefficiency of the Polish stock market seems even stronger as causality from ΔIRT to Δln(WSE) which was established based on the results of both linear and nonlinear Granger causality tests.

Our empirical analysis was also partly based on conducting cointegration causality tests. With the application of significance tests for appropriate cointegration components we managed to establish a long-run bidirectional causality between Δln(WSE) and all the examined macroeconomic variables except for ΔIRT. On the other hand we found strictly unidirectional long-run causality in the direction from changes in interest rate to all other examined variables. Once again the results of the considered causality tests provided a strong basis for claiming that the Polish stock market is informationally inefficient, this time with respect to all examined variables. One must note that if the Polish stock market is indeed informationally inefficient with respect to the set of specific macroeconomic variables, abnormal return may be obtained consistently by using information on the changes in these variables.

The existence of an enormously strong causal relationship between the Δln(WSE) and Δln(PROD) variables confirms the hypothesis that in the case of Poland a knowledge of the main macroeconomic fundamentals of the real economy is a helpful tool in predicting the future performance of the financial sector and vice versa. This outcome is not surprising when we analyze the process of the development of the Polish stock market. The ratio of stock market capitalisation and GDP has vastly increased in the last 15 years – from less than 4% in the mid-1990's to over 31% in the year 2005. As the performance of the stock market became an important indicator of the condition of Polish economy, the relationships between macroeconomic fundamentals and stock prices have received considerable attention. Fluctuations in the real sector cause changes in the financial condition of market participants. On the other hand dramatic events in the stock market are likely to have an impact on the real economy. At this point it is worth noting that conditions for the existence of causality in the direction from stock market index to some macroeconomic variable are favorable, since the news about the performance of the stock market are available every day while most macroeconomic indicators are published just several times per year.

Our findings provide a strong basis for claiming that there exists a bidirectional causal relationship between changes in the unemployment rate and fluctuations in the natural logarithm of sold industrial production. This result was obtained based on the outcomes of both linear and nonlinear causality tests. Furthermore, cointegration and causality analysis led us to establishment of unidirectional long-run causality from Δln(PROD) to ΔUNEMPL. All these facts together with previously described bidirectional dynamic relationship between industrial production and the stock market index are in some respects evidence for the existence of an indirect causal relationship between the unemployment rate and the performance of the Polish stock market (this should be directly indicated after analysis of VECM including more lags).

Furthermore, our research provided strong evidence of causality in the direction from ΔIRT to Δln(WSE) (this was indicated by all types of conducted tests). These findings should be deeply analyzed together with the bidirectional causal relationship between ΔIRT and ΔINFL, which was established by the application of both linear and nonlinear tests. In theory stocks are believed to be a solid barrier against inflation, because a company's earnings should grow at the same rate as the inflation rate. However, one must remember that inflation robs all investors by raising prices with no corresponding increase in value. Thus company's financials are over-stated and decline when inflation decline. On the other hand, the short-term interest rate is a government' instrument for the reduction of inflation. When money is more expensive to borrow, excess capital may be easily removed from the market. Furthermore, an increase in the interest rate leads to an increase in that part of a company's costs which reflects the involvement of foreign capital. As the financial results worsen, less money is available for dividend payouts and company development. Naturally, a decrease in the interest rate causes inverse process. Therefore, it is not surprising that our findings confirmed existence of a net of strong dynamic connections between the stock market index, the short-run interest rate and the rate of inflation.

We hope our effort can help to better understand the relationship between stock markets and some key macroeconomic fundamentals. As the Polish economy is still in a transitory phase, some further investigation should be carried out.

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