JEL Classification: C52, G11, G15, G32
Keywords: interrelations, macroeconomic indicators, G6, financial markets, TVTMP model

# Effects of Macroeconomic Indicators on the Financial Markets Interrelations

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*Abstract*

*Analyses of financial market interrelationships are important for effective portfolio diversification. The interdependencies between markets are stronger during turbulent times on financial markets than during periods of calm. This fact was especially evident during the global crisis. So, the predictability of stock return interrelationships is a topic discussed most-frequently in empirical studies. In this paper, the role of macroeconomics indicators in the dynamic of interrelationships between financial markets will be considered. Effects of the unemployment rate, CPI, long-term interest rate, and industrial production on the comovement between markets from the G6 group will be verified. For this purpose, the Markov-switching copula model with time-varying matrix transition probability (TVPMS) will be adapted. It has been found that the unemployment rate and long-term interest rate are important factors for interrelationships between the Polish market and the developed market from Germany, France or Italy. The long-term interest rate appears to be important for interrelationships between the Poland and British market and between some developed markets.*

## 1. Introduction

Knowledge of the mutual links between different stock markets is crucial for investors and policy makers. The diversification strategies created to reduce the risk of investments are closely tied to the nature and strength of these interrelationships. After the global financial crisis, theorists and practitioners began to pay attention to the co-movements in the international stock markets. Sudden and simultaneous economic slowdowns in many countries around the world have also induced researchers to study the determinants of these co-movements.

Thus, the aim of this paper is to search for the role of macroeconomic indicators in the dynamic of interrelationships between some chosen pairs of stock markets. Our main theoretical contribution is to show that some macroeconomic variables (such as the consumer price index, index of industrial production, long-term interest rate, and unemployment rate) may be determinant of co-movement between markets from the G6 group. We show that changes in the current unemployment rate and long-term interest rate have influence on the state of interdependence between Poland and the developed markets of Germany, France or Italy. The long-term interest rate is also important for interrelationships between the Poland and British market. This factor is also relevant for interdependence between some developed markets.

There has been a lot of research on factors that interact in financial markets, such as political events, the economic situation, and investor expectations (Huang et al., 2005). As the stock market is a part of the economy and stock prices are often determined on a cash flow basis, fundamental macroeconomic indicators can influence stock market prices and be included in portfolio investment decision (Pilinkus, 2010; Chen, 2009; Haq and Larson, 2016). Rapach et al. (2005) presented evidence that stock returns can be predicted using macro variables. Using data from 12 industrialized countries after the 1970s, they showed that interest rates are the most consistent and reliable predictors of stock returns across all of the countries. Chen (2009) investigated whether macroeconomic variables can predict recessions in a stock market. The author evaluated series such as interest rate spreads, inflation rates, money stocks, aggregate output, unemployment rates, federal funds rates, federal government debt, and nominal exchange rates and concluded that bear markets can be easily predicted based on macroeconomic variables. The issue of relationships between stock prices and some economic variables was taken into consideration, among others, by Humpe and Macmillan (2007), Mahmood and Dinniah (2009), Chang (2009). Nasseh and Strauss (2000) showed the existence of a long-run relationship between stock prices and the macroeconomic activity in six major European countries. They concluded that the stock markets were driven by economic fundamentals and interrelated factors such as production, business expectations, interest rates, and the CPI. The existence of long-run equilibrium relationships among stock prices, industrial production, real exchange rates, interest rates, and inflation in the United States was investigated by Kim (2003).

Furthermore, there is a lot of research on the determinants of co-movements between financial markets. For example, using data on sixteen national stock markets, King et al. (1994) concluded that only a small proportion of the time variation in the covariances between national stock markets can be accounted for by observable economic variables. Changes in correlations between markets are driven by movements in unobservable variables. Longin and Solnik (1995), studying the monthly asset excess returns of seven major countries from 1960 to 1990, found that correlations increase with conditional volatility. The economic variables such as dividend yield and interest rates contain information about future volatility and correlation. Von Furstenberg and Jeon (1989) analyzed daily movements in the stock price indices of the US, Japan, Great Britain, and Germany during the period of 1986-88. They used interest rate differentials, exchange rates, and prices of oil and gold as the predetermined variables to explain the co-movement between markets. Didier et al. (2010) analyzed the factors driving the correlation between stock market returns in the US and in 83 other countries for the crisis period of 2007-2008, and they found that only financial factors were important, while macro vulnerabilities did not seem to matter for mutual linkages in the context of the 2007-2008 crisis. Mobarek et al. (2016) investigated the developed countries (Australia, Canada, France, Germany, Hong Kong, Italy, Japan, Sweden, the United Kingdom, and the United States) and emerging countries (Argentina, Brazil, Chile, China, India, Indonesia, Korea, Malaysia, Russia, and South Africa). Studying the time-varying correlations between some advanced and emerging markets for the period of 1999 to 2011, they were checking whether the determinants of the stock markets' co-movements were economic, financial, or cultural. They found that country-specific factors were crisis contingent transmission mechanisms for the co-movements of emerging country pairs and mixed pairs of advanced and emerging countries during the global financial crisis. However, they did not observe the transmission of the crisis among advanced country pairs. Based on the selected ten indicators from Google Trends related to economic activity for the United States and the four European countries, Gomes and Taamouti (2016) created new factors. These factors are correlated with several monthly macroeconomic indicators for all of the countries, particularly with changes in unemployment rate, inflation, or the growth rate of industrial production. These factors extracted from Google search data predict the co-movement in cross-country European stocks.

The subject of mutual linkages was also discussed regarding the markets in Central and Eastern Europe. The existence of long-run relationships between emerging Central European stock markets and the mature stock markets of Europe and the United States have been analyzed by Voronkova (2004). Dynamic linkages between emerging European and developed stock markets was analyzed by Syriopoulos (2007) among others. The important impact of the developed European markets on CEE emerging markets was obtained by Černý and Koblas (2005) and Égert and Kočenda (2007), who showed significant intraday causalities between the returns of CEE markets and causal relationships from the developed to the emerging markets. On the other hand, Égert and Kočenda (2011) found very few positive time-varying correlations between the intraday returns of the BUX, PX50, and WIG20. Relationships between macroeconomic fundamentals and stock market indices in selected CEE countries was studied by Barbic and Condic-Jurkic (2011), among others. The reaction of asset prices to macroeconomic announcements on the new EU markets was verified by Hanousek, Kočenda, and Kutan (2009). The impact of US macroeconomic news announcements on the relationships between returns, volatility, and turnover on the three European stock markets operating in Frankfurt, Vienna, and Warsaw was considered by Gurgul, Lach, and Wojtowicz (2016).

In the literature, plenty of models have been proposed to verify the interdependence between stock asset returns, such as the dynamic conditional correlation model of Engle (2002), the regime-switching dynamic correlation model proposed by Pelletier (2006), or the regime-switching copula model (Patton, 2006, 2009). The regime-switching copula model with a Markov switching mechanism for modeling financial time series has also been discussed by Jondeau and Rockinger (2006), Rodriguez (2007), Okimoto (2008), Chollete et al. (2009), Silva, Ziegelmann, and Dueke (2012), and others.

Determinants of time varying co-movements among international stock markets can be studied using the DCC-MIDAS model described by Colacito et al. (2011), for example. This approach was used by Mobarek et al. (2016). To study the impact of some factors on market interrelationships, the time-varying transition probability Markov-switching (TVPMS) copula model can also be adapted. The TVPMS framework was originally proposed by Filardo (1994) and further extended by Kim et al. (2008). Among others, the Markov-switching copula model with TVPMS mechanism was used by Boudt et al. (2012), who studied the impact of VIX or Ted spread on the interdependencies between weekly returns on US-headquartered bank holding companies.

The contribution of this paper is to verify the thesis that changes in some macroeconomic variables (such as the consumer price index, index of industrial production, long-term interest rate, and unemployment rate) may be important for the state of interdependence between two given markets. From these purposes, the daily returns of six main indices and monthly data of the macroeconomic variables from the period of January 2006 to January 2017 are taken into consideration. The linkages between the daily returns of indices coming from G6 markets are described using the Markov-switching copula model. To verify the influence of some macroeconomic indicators on the interrelationships between some chosen pairs of stock markets, the Markov-switching copula model with a TVPMS mechanism is used. We came to the conclusion that current changes in the macroeconomic variables, such as the unemployment rate or and long-term interest rate, are important mainly for the interrelationship between the Polish market and the other G6 markets (with the exception of Spain or Great Britain), but for the interrelationship between some developed markets and between Polish market with a British one, the only long-term interest rate is important.

This paper is organized as follows. Section 2 describes the marginal model specification and copula model controlled by the time-varying transition probability Markov-switching framework. Section 3 presents the empirical results of the study of dependencies between the markets indices of the G6 group. Finally, Section 4 contains the conclusions of the study.

## 2. Econometric Framework

### 2.1 Marginal Model Specification

In the case of financial time series modeling, the $GARCH(1,1)$ model proposed by Bollerslev (1986) is the simplest and the most-popular parameterization. However, the GARCH effect is not always justified by the data. Thus, two additional properties of the returns need to be considered. The first is associated with the autocorrelation of the time series. At the same time, the autocorrelation of stock returns vanishes very rapidly for higher lags, so it is sufficient in most practical applications to include only one autocorrelation term. The second property is that the effect of positive and negative returns on the variances differs in terms of its magnitude. So, we consider the ARMA (1,1)-GJR-GARCH(1,1) model:

$$R_t = a + bR_{t-1} + \varepsilon_t + \theta\varepsilon_{t-1}, \tag{1}$$

where $\varepsilon_t = \sigma_t \eta_t$ and $\sigma_t^2 = a_0 + \beta_1 \sigma_{t-1}^2 + \alpha_1 \varepsilon_{t-1}^2 + \alpha_2 I_{(\varepsilon<0)} \varepsilon_{t-1}^2$.

We assume that the conditional distribution of $\varepsilon_t$ is a skewed t-Student with $\nu$ degrees of freedom.

To evaluate the goodness-of-fit of such defined marginal distributions, we use the diagnostic test of Diebold et al. (1998). Let $F$ be the conditional cumulative distribution functions of $R_t$ and let $\mathcal{R}_{t-1}$ denote the information set at period $(t-1)$. If a marginal distribution is correctly specified, $u_t = F(r_t|\mathcal{R}_{t-1};\theta_1)$ should be i.i.d. uniform [0, 1] distributed.

The test is performed in two steps:

1) We evaluate whether $u_t$ is serially independent. Upon doing this, we separately examine serial correlation $z_{tk} = (u_t - \bar{u})^k$ for $k = 1,\ldots,4$ on 20 of our own lags. The $k$-th test statistic is defined as follows:

$$R(k) = (T - 20)R^2, \tag{2}$$

where $R^2$ is the coefficient of the determination of the regression. It is distributed as an $\chi^2_{20}$ under the null hypothesis.

2) We test the null hypothesis that $u_t$ is uniform [0, 1] distributed.

### 2.2 The TVPMS Copula Model

A Copula function describes the flexible dependence structure between two random variables. According to Sklar's theorem (Sklar, 1959) for a joint distribution function, the marginal distributions and dependence structure represented by Copula function $C$ can be separated. Let $R_{1,t}$ and $R_{2,t}$ be two random variables denoting two different asset returns at time t, and let $S_t$ be a hidden Markov process with two states $(1,2)$. The conditioned distribution of $(R_{1,t}, R_{2,t})$ has the following form:

$$F(r_{1,t}, r_{2,t} | S_t = j, \mathcal{R}_{t-1}; \boldsymbol{\theta}) = C(u_t, v_t | S_t = j, \mathcal{R}_{t-1}; \theta_c^j), \tag{3}$$

where $u_t = F_1(r_{1,t} | \mathcal{R}_{t-1}; \theta_1), v_t = F_2(r_{2,t} | \mathcal{R}_{t-1}; \theta_2)$, and $C(\cdot)$ is a conditional copula.

In the TVPMS copula model we assume, that transition matrix $P_t$ in a hidden Markov process is defined as follows:

$$P_t = \begin{bmatrix} p_t^{11} = \frac{exp(x_{t-1}^T \beta_1)}{1 + exp(x_{t-1}^T \beta_1)} & p_t^{12} = 1 - \frac{exp(x_{t-1}^T \beta_1)}{1 + exp(x_{t-1}^T \beta_1)} \\ p_t^{21} = 1 - \frac{exp(x_{t-1}^T \beta_2)}{1 + exp(x_{t-1}^T \beta_2)} & p_t^{22} = \frac{exp(x_{t-1}^T \beta_2)}{1 + exp(x_{t-1}^T \beta_2)} \end{bmatrix}, \tag{4}$$

where $p_t^{ij} = P(S_t = j | S_{t-1} = 1)$, a time-varying transition probability that state $j$ will be followed by state $i$ at time $t$ evolves as a logistic function of $x_{t-1}^T \beta_i$. Matrix $x_{t-1}^T$ contains economic variables that affect these transition probabilities.

For the purpose of comparison, we also consider the fixed probability copula model as a benchmark. If there is no statistically meaningful impact of the macroeconomic variables on interdependencies between the markets, then the TVPMS copula model converges to the Markov-switching copula model with fixed transition probabilities, (MS copula model).

The model with fixed probabilities is nested in the model with time - varying probabilities. For nested models testing the hypothesis that the considered models are equivalent against the hypothesis that one model is better than the other, the Vuong test statistic could be applied (Vuong 1989). The test statistic is: $LM = 2(\ell(\theta) - \ell_F(\theta_1))$, where $\ell(\theta)$ and $\ell_F(\theta_1)$ are the log-likelihood function of the models with time-varying and fixed transition probabilities, respectively. The asymptotic distribution of this statistic reduces to the central chi-square one (White, Domiwitz [1984]; Vuong [1989]).

### 2.3 The Procedure of Estimation Markov-Switching Copula Model Parameters

The estimation of the unknown model parameters is performed in two steps. First, the parameters of the marginal models are estimated using the maximum likelihood method to obtain $\hat{\theta}_1$ and $\hat{\theta}_2$. The other parameters are estimated using Hamilton filters (Hamilton, 1990). Let $\boldsymbol{\theta}$ denote the collected copulas' parameters and parameters of the transition probabilities: $\beta_1$, $\beta_2$ . Log-likelihood function $\ell_c(\boldsymbol{\theta})$ has the form:

$$\ell_c(\boldsymbol{\theta}) = \sum_{t=1}^{T} \log\left(\sum_{j=1}^{2} c_j\left(\widehat{\boldsymbol{F}}_t \middle| \mathcal{R}_{t-1}; \theta_c^j\right) P(S_t = j|\mathcal{R}_{t-1}; \boldsymbol{\theta})\right), \tag{5}$$

where $\widehat{\boldsymbol{F}}_t = \left(F_1\left(r_{1,t}\middle|\mathcal{R}_{t-1}; \hat{\theta}_1\right), F_2\left(r_{2,t}\middle|\mathcal{R}_{t-1}; \hat{\theta}_2\right)\right)$ and $c_j(\cdot)$ is the copula density in the $j$ −th state. Let $\eta_t$ denote a vector of two copula densities governed by the Markov process at date $t$: $\eta_t = \left[c_1\left(\widehat{\boldsymbol{F}}_t\middle|\mathcal{R}_{t-1}; \theta_c^1\right), c_2\left(\widehat{\boldsymbol{F}}_t\middle|\mathcal{R}_{t-1}; \theta_c^2\right)\right]^T$ and let $\hat{\xi}_{t|t-1}$ denote collected conditional probabilities $P(S_t = j|\mathcal{R}_{t-1}; \boldsymbol{\theta})$: $\hat{\xi}_{t|t-1} = [P(S_t = 1|\mathcal{R}_{t-1}; \boldsymbol{\theta}), P(S_t = 2|\mathcal{R}_{t-1}; \boldsymbol{\theta})]^T$.
The optimal inference and forecast for each $t$ in the sample can be found by iteration using the pair of equations:

$$\hat{\xi}_{t|t} = \frac{\hat{\xi}_{t|t-1} \odot \eta_t}{1^T(\hat{\xi}_{t|t-1} \odot \eta_t)}, \qquad \hat{\xi}_{t|t+1} = P_{t+1}^T \hat{\xi}_{t|t}. \tag{6}$$

Hence, symbol $\odot$ denotes the element by element multiplication. The log-likelihood function $\ell_c(\boldsymbol{\theta})$ has the form:

$$\ell_c(\boldsymbol{\theta}) = \sum_{t=1}^{T} \log\left(1^T\left(\hat{\xi}_{t|t-1} \odot \eta_t\right)\right). \tag{7}$$

The parameter estimators of standard Markov-switching copula model are performed in the same way, but instead of time-varying transition matrix, we take matrix with fixed transition probabilities. To evaluate the goodness-of-fit of the Markov-switchimg copula model we use the diagnostic test (Changqing, 2015). Let us assume that the corresponding copula is $C(\cdot)$. Then, the conditional distribution of random variable $V$ defined as:

$$C_u(v) = C(V \leq v|U = u) = \frac{\partial}{\partial u} C(u, v) \tag{8}$$

obeys the [0,1] uniform distribution.

So, to examine the preciseness of the dependency structure of the returns, we test whether the first-order partial derivatives of function

$$C(u_t, v_t|, \mathcal{R}_{t-1}; \boldsymbol{\theta}) = 1^T\left(\hat{\xi}_{t|t-1} \odot \eta_t\right) \tag{9}$$

is uniform$[0, 1]$ distributed

## 3. Empirical Study

### 3.1 Data

The investigation covers market indices from the G6 group. The G6 is a group of six European Union member states with the largest populations – Germany, the UK, France, Italy, Spain, and Poland. The G6 was established in 2003 as the G5 and was formed by five well-developed, leading industrial countries in Western Europe. In 2006 Poland joined the group, making it the G6. However, Poland is still considered an emerging market.

The following indices were considered: WIG (Poland), DAX (Germany), FTSE (UK), IBEX (Spain), CAC (France), and FTSE MIB (Italy). Any missing data was interpolated. The daily returns were computed as the difference between the logarithm of value on day $t$ and the logarithm of value on day $(t-1)$. Daily values of the indices came from the period of January 2006 to January 2017[1]. All returns have been converted to Euros.

Table 1 presents the basic descriptive statistics for all return indices: average, median, standard deviation, skewness, and kurtosis. One can see from Table 1 that the average of the returns range from –0.016% to 0.032%. The largest average (0.032%) is for the German index returns, whereas the lowest – for the Italian (-0.016%). The average of the Poland index returns is 0.019%, which places it in third place (after the German and British). For all cases, the median is greater than the average and the skewness is negative, so the left-skewed distribution of the analyzed time series should be considered. A high kurtosis that accepts values from 4.342 to 8.113 should also be taken into account.

**Table 1 Descriptive Statistics of Data**

| *country* | *Average* | *Median* | *Std.deviation* | *Skewness* | *Kurtosis* |
|---|---|---|---|---|---|
| France | 0.008 | 0.042 | 1.432 | -0.004 | 6.327 |
| Germany | 0.032 | 0.108 | 1.382 | -0.041 | 6.122 |
| the UK | 0.025 | 0.083 | 1.291 | -0.860 | 8.113 |
| Italy | -0.016 | 0.059 | 1.617 | -0.239 | 5.354 |
| Spain | 0.001 | 0.076 | 1.521 | -0.132 | 7.451 |
| Poland | 0.019 | 0.060 | 1.559 | -0.432 | 4.342 |

*Notes:* Average, median, and standard deviation are in percentiles. Kurtosis is taken as $\frac{M_4}{s^4} - 3$, where $M_4$ is the center moment of the fourth order.

The macroeconomic variables used in the empirical study represent the economic condition of each country. For the analyzed pairs of countries, we used information about the following macroeconomic factors: the long-term interest rate (LTI), consumer price index (CPI), industrial producer price index (IP), and unemployment rate (UNEMP)[2]. We take into account the data quoted at the end of each month. The consumer price index and industrial producer price index measure the percentage of change as compared to the same period of the previous year. The long-term interest rate is the monthly data taken as a Maastricht criterion interest rate[3].

[1] Data comes from www.stooq.com
[2] Data comes from Eurostat Database. The Eurostat methodological guidelines ensure the comparability between the national statistical data
[3] The Maastricht Treaty EMU convergence criterion series relates to interest rates for long-term government bonds denominated in national currencies. The selection guidelines require the data to be based on central

The unemployment rate is the number of unemployed persons as a percentage of the labor force (the total number of people employed and unemployed). This data is expressed in percentages and is seasonally adjusted.

Table 2 presents the averages and standard deviations of the macroeconomic variables.

**Table 2 Averages and Standard Deviation of Macroeconomic Data**

| | | *France* | *Germany* | *The UK* | *Italy* | *Spain* | *Poland* |
|---|---|---|---|---|---|---|---|
| LTI | *Average* | 3.16 | 2.751 | 3.344 | 4.256 | 4.196 | 5.168 |
| | *Std.deviation* | 0.950 | 1.139 | 1.204 | 0.939 | 1.024 | 1.009 |
| CPI | *Average* | 1.606 | 1.672 | 2.651 | 1.956 | 2.172 | 2.452 |
| | *Std.deviation* | 0.975 | 0.899 | 1.032 | 1.141 | 1.662 | 1.578 |
| IP | *Average* | 1.545 | 1.591 | 4.006 | 1.912 | 2.663 | 1.908 |
| | *Std.deviation* | 2.945 | 2.618 | 6.406 | 3.38 | 3.374 | 2.921 |
| UNEMP | *Average* | 9.311 | 6.642 | 6.247 | 9.357 | 17.759 | 9.635 |
| | *Std.deviation* | 0.892 | 2.176 | 1.329 | 2.305 | 6.315 | 3.248 |

*Notes:* LTI is monthly data taken as a Maastricht criterion interest rate. CPI and IP measure the percentage ch ange compared to the same period in the previous year. The unemployment rate is the number of unem ployed persons as a percentage of the total number of people employed and unemployed. This data is e xpressed in percentages and is seasonally adjusted.

The highest average of LTI is in Poland (5.168%) whereas the lowest is in Germany (2.751%). The average of the Spanish LTI is similar to that of Italy's (close to 3%), while the British LTI is similar to France's (close to 4%). In all cases, the standard deviation reaches the same level, and it is about one percent. The average CPI is highest in the UK (averaging 2.651% with a standard deviation of 1.032%) and lowest in Germany (averaging 1.672% with a standard deviation of 0.899%). In Poland, this is equal to 2.452% (with a standard deviation of 1.578%); this is close to the Britain's (for the British CPI, the average is equal to 2.651%, but the standard deviation is less than in Poland, equaling 1.039%). On average, the industrial producer price index is highest in the UK, but it is also very diverse there (the average is 4.006%, and the standard deviation is equal to 6.406%). The IP averages in France and Germany are very similar to each other (about 1.5%). Also, in Poland and Italy, the IP averages are approximately the same (1.9%, with a standard deviation of 3%). In Table 2, we can also observe that the unemployment rate is the highest in Spain (average – 17.759%; standard deviation – 6.315%) and lowest in Germany (average – 4.642%; standard deviation – 2.176%). The average of the unemployment rate in Poland is similar to that of France and Italy (close to 9%); however, in Poland, the standard deviation is relatively high (3.248 percent).

government bond yields on the secondary market, gross of tax, with a residual maturity of around ten years. The bond or bonds of the basket must be replaced regularly to avoid any maturity drift.

**Table 3 Correlations Between Differentiated Data of LPI, IT, CPI, and Unemployment**

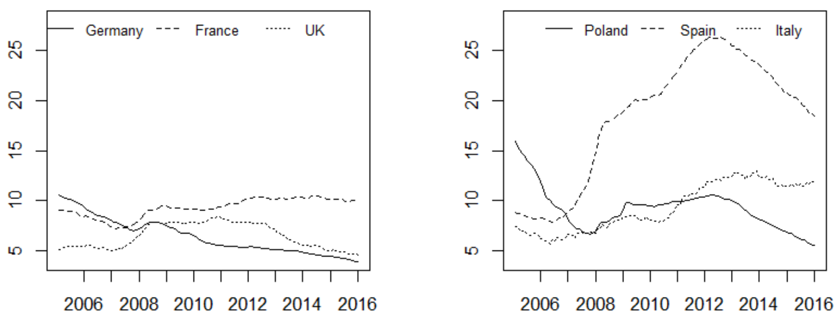
| | ***France*** | ***Germany*** | ***the UK*** | ***Italy*** | ***Spain*** | ***Poland*** |
|---|---|---|---|---|---|---|
| | | | *LTI* | | | |
| *France* | 1.000 | | | | | |
| *Germany* | 0.854 | 1.000 | | | | |
| *the UK* | 0.709 | 0.804 | 1.000 | | | |
| *Italy* | 0.585 | 0.304 | 0.213 | 1.000 | | |
| *Spain* | 0.616 | 0.380 | 0.306 | 0.823 | 1.000 | |
| *Poland* | 0.556 | 0.450 | 0.418 | 0.490 | 0.435 | 1.000 |
| | | | *CPI* | | | |
| *France* | 1.000 | | | | | |
| *Germany* | 0.607 | 1.000 | | | | |
| *the UK* | 0.397 | 0.371 | 1.000 | | | |
| *Italy* | 0.539 | 0.411 | 0.343 | 1.000 | | |
| *Spain* | 0.631 | 0.687 | 0.446 | 0.441 | 1.000 | |
| *Poland* | 0.319 | 0.163 | 0.106 | 0.195 | 0.189 | 1.000 |
| | | | *IP* | | | |
| *France* | 1.000 | | | | | |
| *Germany* | 0.754 | 1.000 | | | | |
| *the UK* | 0.610 | 0.552 | 1.000 | | | |
| *Italy* | 0.811 | 0.736 | 0.479 | 1.000 | | |
| *Spain* | 0.750 | 0.691 | 0.629 | 0.759 | 1.000 | |
| *Poland* | 0.130 | 0.186 | 0.105 | 0.147 | 0.164 | 1.000 |
| | | | *UNEMP* | | | |
| *France* | 1.000 | | | | | |
| *Germany* | 0.432 | 1.000 | | | | |
| *the UK* | 0.396 | 0.148 | 1.000 | | | |
| *Italy* | 0.165 | 0.184 | -0.004 | 1.000 | | |
| *Spain* | 0.483 | 0.208 | 0.499 | 0.262 | 1.000 | |
| *Poland* | 0.424 | 0.449 | 0.222 | 0.249 | 0.426 | 1.000 |

*Notes:* The stationary of each part of the macroeconomic data has been verified by the ADF test. Because they are not stationary, the difference of the first order is used. In the table, the correlation between the data is presented. The stationarity of each part of the macroeconomic data has been verified using the ADF t est. Since the results of the test did not confirm their stationarity, the difference of the first order that was determined for each part of the data is taken for further calculations.

Table 3 presents the correlations between the increments of LPI, IT, CPI, and unemployment. A relatively high correlation between the LPI coming from France, the UK, and Germany can be observed (more than 0.709). The remaining pair of markets for which a high LPI correlation is observed is the pairing of Italy and Spain (0.823). The rest of the correlation coefficients are at a rather moderate level (from 0.213 to 0.616). The correlation coefficients between the CPI of all countries are relatively low. The highest value of this coefficient is observed for Germany's and Spain's CPI (0.687), France's and Spain's (0.631), and Germany's and France's (0.607). On the other hand, the lowest value of this coefficient is observed between the Polish and British CPIs (0.106). The industrial producer price indices are relatively highly correlated but only when they come from the Eurozone; i.e., from Germany, Spain, France, or Italy (the highest correlation coefficient is for the Italian and French IP, which equal 0.811, and the lowest for the German and Spanish IP: 0.691). The Polish IP is very weakly correlated with the others. For these cases, the highest correlation coefficient equals only 0.186 (for the Polish and German IP). Finally, we can notice that all correlation coefficients calculated for the unemployment rate are low. The greatest value is only 0.499 (Spain and the UK). These correlation coefficients vary from 0.148 to 0.499.

After considering several macroeconomic variables that may be related to the probability of transition between two regimes, we will note that only the unemployment rate and long-term interest rate are significant. So, Figure 2 presents the dynamics of changes in unemployment for all of the analyzed countries; for Germany, France, and the UK (left panel) and Poland, Spain, and Italy (right panel).

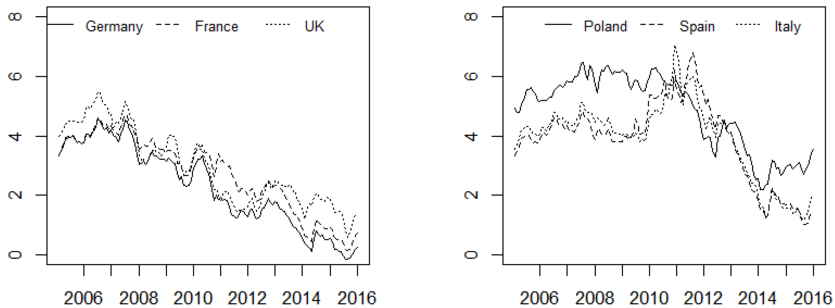
**Figure 1 Unemployment Variables for Germany, France, and the UK (eft panel) and Poland, Spain, and Italy (right panel)**




By analyzing the graphs in Figure 1, we note that the lowest unemployment is in Germany, while the highest is in Spain. Furthermore, unemployment in Germany, France, and the UK is characterized by relatively small dynamics of changes, whereas in Poland, Italy, and Spain, we can observe rather large fluctuations. Thus, as it turned out in the study, changes in unemployment in these last three countries played a significant role in the relationships between the respective stock exchanges.

Figure 2 presents the dynamics of change in long-term interest rates for Germany, France, and the UK (left panel) and Poland, Spain, and Italy (right panel).

**Figure 2 Long-Term Interest Rate for Germany, France, and the UK (left panel) and Poland, Spain, and Italy (right panel)**




The long-term interest rate in Germany, France and the United Kingdom has a downward trend, while in Spain and Italy, it was subject to strong fluctuations. In Poland, we also observe a downward trend; however, the fluctuations in the rates of return are definitely higher than for Germany, France, and the UK. It seems that, after 2014, we notice a slight increase in interest rates in Poland. However, despite the relatively small changes in the interest rates of Germany, France, and the United Kingdom, it is these rates that are important for the strength of the links between exchanges.

## 3.2 Results

### 3.2.1 Diagnostic tests results

In the preliminary step of our empirical work, we investigate the structure of the univariate marginal returns. The model suggested for the description of the returns is based on the autocorrelation and heteroskedasticity test results. As mentioned earlier, ARMA(1)- GJR-GARCH(1, 1) with skewed t-Student conditional distribution is considered to describe the modeling of the returns. Thus, the procedure of testing the goodness-of-fit is carried out. For testing purposes, the procedure described in Diebold et al. (1998) was followed. Table 4 reports the $p-values$ of the goodness-of-fit statistics.

**Table 4 P-Values for Test Specification**

| *country* | *p(1)* | *p(2)* | *p(3)* | *p(4)* | *p* |
|---|---|---|---|---|---|
| *France* | 0.269 | 0.999 | 0.147 | 0.996 | 0.223 |
| *Germany* | 0.405 | 0.97 | 0.436 | 0.976 | 0.153 |
| *the UK* | 0.359 | 0.011 | 0.53 | 0.035 | 0.524 |
| *Italy* | 0.610 | 0.703 | 0.618 | 0.820 | 0.281 |
| *Spain* | 0.172 | 0.776 | 0.39 | 0.676 | 0.192 |
| *Poland* | 0.493 | 0.441 | 0.687 | 0.361 | 0.765 |

*Notes:* p(k) - p-values for the null hypothesis of no serial correlation of the k-th centered moments; p are p-values for the Anderson-Darling test statistics for the null hypothesis that the cdf of the residuals is uniform [0, 1].

The first four columns contain $p$-values labeled as $p(k)$ of $R(k)$ under the null hypothesis of no serial correlation of the k-th centered moments of the $u_t$. The next column reports $p$-values for the test statistics under the null hypothesis that the cumulative distribution function of residuals is uniform [0, 1]. The considered time series test results confirm the correctness of the chosen model. For all cases, we obtained $p \geq 0.05$; therefore, we can assume that, for each $i$, $(i = 1,..,6)$, $u_{i,t} = F_i\left(r_{i,t} \middle| \mathcal{R}_{t-1}; \hat{\theta}_i\right)$ is uniform [0, 1]. Evaluating whether $u_{i,t}$ is serially independent, we also obtained all $p(k) \geq 0.05$. Only for the test specification of returns from the UK we assumed a significance level of 0.01.

**Table 5 P-Values of Goodness-of-Fit Test for MS Copula Model**

| *Country* | *France* | *Germany* | *The UK* | *Italy* | *Spain* | *Poland* |
|---|---|---|---|---|---|---|
| France | - | 0.121 | 0.493 | 0.455 | 0.288 | 0.348 |
| Germany | 0.121 | - | 0.307 | 0.407 | 0.638 | 0.619 |
| UK | 0.493 | 0.307 | - | 0.409 | 0.651 | 0.257 |
| Italy | 0.455 | 0.407 | 0.409 | - | 0.117 | 0.284 |
| Spain | 0.288 | 0.638 | 0.651 | 0.117 | - | 0.399 |
| Poland | 0.348 | 0.619 | 0.257 | 0.284 | 0.399 | - |

*Notes:* Each cell contains the p-value of the Anderson-Darling test that checks whether the distribution of the $C_u$ (v) follows the uniform [0,1].

The aim of applying the above procedure is to improve the quality of fitting the model to the data in order to obtain the uniform distribution necessary to carry out the estimation of the Markov switching copula model. Based on the results of Czapkiewicz and Majdosz (2014), we switch two t-Students copula, obtaining a t-Student-t-Student copula model for the following research[4]. To evaluate the goodness-of-fit of this model, the test described the in previous section was carried out. Table 5 presents the p-values of this test procedure. As we can see, we obtained $p - value \geq 0.05$ for all pairs, so the switching model between the two t-Students copula is appropriate for a follow-up study.

The effects of the unemployment rate, CPI, long-term interest rate, and industrial production on the interdependence between the two markets considered from the G6 group will be verified using the Markov switching two-regime copula model with time-varying matrix transition probability (TVTMP model). Time-varying transition probabilities $p_t^{ii}$ , $i = 1,2$, are evolved in a further analysis as the logistic function of $x_{t-1}^T \beta_i$, where:

$$x_{t-1}^T \beta_i = \beta_0^i + \sum_{j=1}^2 \beta_{L_j}^i L_{j,t-1} + \sum_{j=1}^2 \beta_{C_j}^i C_{j,t-1} + \sum_{i=1}^2 \beta_{I_j}^i I_{j,t-1} + \sum_{j=1}^2 \beta_{U_j}^i U_{j,t-1}. \tag{10}$$

[4] When the degrees of freedom in the t-Student copula is large enough, we take a normal copula into account.

The long-term interest rate is denoted as $L_j$, the consumer price index as $C_j$ , the industrial producer price index as $I_j$, and the unemployment rate as $U_j$, where subscript $j$ $(j = 1,2)$ denotes the first or second analyzed financial market.

If there is no statistically meaningful impact of the macroeconomic variables on the interdependencies between markets, then the TVPMS copula model converges to the MS copula model. So, for each case, we tested the null hypothesis of the Markov-switching model with fixed transition parameters against the alternative of the model with time-varying transition parameters.

The data to study the interrelationships between index returns are daily frequency, whereas the macroeconomic data is monthly frequency. Since the publication of these macroeconomic variables occur at the end of each month, we consider two cases. In the first case, we consider the last-announced data in a given month to check if the known information impacts the interrelationships between markets in the next month (Case I). In the second case, we test whether the values announced at the end of a given month impact the interrelationships between markets during that month (Case II). So, in the last case, we rather discuss any co-movement between markets interdependence and the economic situation depicted by the long-term interest rate, consumer price index, industrial producer price index, and unemployment rate.

The results of the p-values for both cases are reported in Table 6. For comparison, we presented the results of the study for Case II in the appendix when the exchange rate is not included in the returns. The results are slightly different. A comparison of the results for Case I and Case II (in the case of data converted to EUR) collected in Table 6 leads to the conclusion that actual macroeconomic indicators may be important for the state of interdependence between two given markets. For Case I, only the interdependences between the British and Italian markets and between the Polish and Italian markets are better explained by the TVPMS copula model. But in Case II, there are a lot of pairs for which the p-value obtained as a result of a test the null hypothesis of a standard MS copula model against the TVPMS copula model is less than 10%. The interdependence between the Polish market and others (except Spain's), between the British market and others (except Germany's), between the Italian market and others (except France's and Spain's), and between the French and Spanish markets is better explained by the model with a time-varying transition probabilities.

**Table 6 P-Values of LM Test**

| | | | ***CASE I*** | | | |
|---|---|---|---|---|---|---|
| | *France* | *Germany* | *The UK* | *Italy* | *Spain* | *Poland* |
| *France* | | 0.966 | 0.593 | 0.721 | 0.547 | 0.750 |
| *Germany* | 0.966 | | 0.168 | 0.560 | 0.126 | 0.508 |
| *The UK* | 0.593 | 0.168 | | **0.024** | 0.148 | 0.308 |
| *Italy* | 0.721 | 0.560 | **0.024** | | 0.961 | **0.046** |
| *Spain* | 0.547 | 0.126 | 0.148 | 0.961 | | 0.301 |
| *Poland* | 0.750 | 0.508 | 0.308 | **0.046** | 0.301 | |

| CASE II | | | | | | |
|---|---|---|---|---|---|---|
| | *France* | *Germany* | *The UK* | *Italy* | *Spain* | *Poland* |
| *France* | | 0.984 | **0.036** | 0.184 | **0.045** | **0.076** |
| *Germany* | 0.984 | | 0.356 | **0.054** | 0.528 | **0.001** |
| *The UK* | **0.036** | 0.356 | | **0.004** | **0.026** | **0.087** |
| *Italy* | 0.184 | **0.054** | **0.004** | | 0.128 | **0.098** |
| *Spain* | **0.045** | 0.528 | **0.026** | 0.128 | | 0.419 |
| *Poland* | **0.076** | **0.001** | **0.087** | **0.098** | 0.419 | |

*Notes:* Testing the null hypothesis of the Markov switching model with fixed transition parameters (MS) against the alternative of the model with time-varying transition parameters (TVPMS). The test statistic is $\mathrm{LM} = 2\big(\ell(\theta) - \ell_{\mathrm{F}}(\theta_1)\big)$ , where $\ell(\theta)$ and $\ell_{\mathrm{F}}(\theta_1)$ are the log-likelihood function of the model with dynamic probabilities and the model with fixed probabilities, respectively.

A detailed analysis was focused on the interrelationships between the stock exchanges of Germany, the UK, and Poland with the others markets discussed above. These three markets were chosen as distinguished examples: Germany is the country with the strongest economy in Europe, the London Stock Exchange is the largest in Europe, and the Polish stock market represents an emerging market.

### 3.2.2 Estimates of Parameters of the TVTMP Copula Model

The TVTMS model parameter estimates and their significance are reported in Table 7. The significance of the model parameters is verified via the Monte Carlo method, which was performed only for the cases where the TVPMS model is better than MS (p-values are less than 0.10). For all pairs, we obtained statistically significant copula parameters $\rho_i$, i=1, 2, which define the two states of the interdependencies between stock markets: the stronger and weaker ones.

We start the discussion with the presentation of the research results on the interrelationships of the German stock market with others. The interdependence between the German and French markets is very strong in both states ( $\rho_1 = 0.963, \rho_2 = 0.884$). Statistic $LM = 6.352$ with $p - value = 0.984$, so we have not verified the impact of the macroeconomic values on their mutual dependencies. The two states are also observed for the German and British stock markets; however, the relationship between these two markets is slightly weaker than in the previous case ($\rho_1 = 0.827, \rho_2 = 0.622$). Similar to the previous case, we also observe a low value of the $LM$ statistic and $p - value \geq 0.1$, so we have not confirmed the influence of the macroeconomic values for the strength of the interrelationship between these two markets either. The correlation between the German and Italian stock exchanges is very close to that between the German and Spanish ones. For the first pair of markets, $\rho_1 = 0.913, \rho_2 = 0.679$, whereas for the second, $\rho_1 = 0.917, \rho_2 = 0.723$. Let us pay attention to the fact that the LM is relatively high (and $p - value\ = 0.054$) only for the pairing of the German and Italian markets, which proves the significant influence of the macroeconomic variables for their interdependence. The statistical significance of some of the coefficients of Formula (10) collected in Table 7 shows the influence of the German long-term interest rate on probability $p_t^{22}$. The sign of parameter $\beta_{L_1}^2$ ( $\beta_{L_1}^2 = 1.792$) indicates that an increase in rates weakens the mutual relationships between these two markets. Another pairing of markets for which the macroeconomic variables are important for the linkages between them is the pair consisting of the German and Polish stock exchanges (p$-value = 0.001$), which will be discussed later.

Now, let us discuss the interrelationship of the British market with others. The correlation between the British and French markets is similar to that between the British and German markets ($\rho_1$ = 0.844 and $\rho_2$ = 0.638). For the first pair, we have confirmed the influence of the macroeconomic variables on their mutual interdependence ($p - value = 0.036$). Positive parameters $\beta_{L_1}^2 = 2.129$ and $\beta_{L_2}^2 = 0.526$ inform us about the coincidence in the changes of probabilities $p_t^{22}$ with long-term interest rates taking from both countries. The interdependence of the British stock exchange with the Italian or Spanish market is slightly weaker than discussed above (for Italy's – $\rho_1$ = 0.791, $\rho_2$ = 0.502; whereas, for Spain's – $\rho_1$ = 0.793, $\rho_2$ = 0.433). For each pair, the $p - value$ is less than 0.01 ($p - value = 0.004$ for Italy and $p - value = 0.026$ for Spain). The significance of the suitable beta coefficients have shown the importance of the interest rate for these two discussed interdependences. Similar to the results obtained from the British and French interdependence study, two positive parameters (for the Italian stock market – $\beta_{L_1}^2 = 2.754$ and $\beta_{L_2}^2 = 3.832$, whereas for the Spanish stock market – $\beta_{L_1}^2 = 1.928$ and $\beta_{L_2}^2 = 1.852$) indicate the same direction of changes in probabilities $p_t^{22}$ as the changes in long-term interest rates. Additionally, for the UK and Spain, unemployment affects probability $p_t^{11}$ ( $\beta_{U_1}^1 = 1.356$ and $\beta_{U_2}^1 = 1.517$). The relationship between the British and Polish stock exchanges ($p - value = 0.089$) will be discussed below.

Turning now to the interrelationships between an emerging market and the others, we discuss the results obtained from the study of interdependence between Polish market and the others. We note that, for all analyzed pairs, the corresponding correlation parameters are at a similar level (both in regime 1 and regime 2). In the first state, correlation parameter $\rho_1$varies from 0.718 (with British stock markets) to 0.748 (with German or French markets), whereas second state parameter $\rho_2$ varies from 0.373 (for the German market) to 0.457 (Spanish). For almost all of the pairings (except with Spain), the obtained $p - values$ indicate that the model with the time varying transition parameters fit the data better than the model with fixed transition parameters. A sign of parameter $\beta$ connected with a given macroeconomic variable determines the direction of change of the probability of staying in the first or second regime, respectively. After the consideration of several macroeconomic variables that may be associated with the probability of switching between two regimes, we can notice that the unemployment plays a crucial role nearly everywhere. The parameters of $\beta_{U_1}^1$or $\beta_{U_2}^1$ associated with unemployment are significant for all analyzed cases. The unemployment rate in Poland is significantly associated with the probability of being in the regime of strong dependence for models with corresponding countries such as France ($\beta_{U_1}^1 = 1.719$) and Germany ($\beta_{U_1}^1 = 2.243$). For Italy, we observe both significant parameters, $\beta_{U_1}^1 = 1.510$ and $\beta_{U_2}^1 = 3.014$ . The growing rate of unemployment can be a suitable indicator for the growing probability $p_t^{11}$ of staying in the first regime. This result is in accordance with theoretical expectations. Unemployment is a strong determinant of the condition of the economy, and its rapid growth may indicate the economic downturn of a given country. It seems that, as compared with other countries, the level of unemployment in the less-powerful Polish economy coincides with changes of the state transition probabilities.

For the discussed relationships of the Polish market with others, the probability of staying in the regime with a weak dependence (State 2) is associated with the long-term interest rate. Parameters $\beta_{L_2}^{2}$ related to these macroeconomic variables are statistically significant for all developed markets (for France – $\beta_{L_2}^{2} = 2.363$; for Germany – $\beta_{L_2}^{2} = 1.071$; for the UK – $\beta_{L_2}^{2} = 7.829$; and for Italy – $\beta_{L_2}^{2} = 1.596$). Thus, an increase in the long-term interest rate has an impact on increasing transition probability $p_t^{22}$. We can therefore assume that this is related to the fact that, if the long-term interest rate in a given country is high enough, then investors are reluctant to invest in risky stock markets (particularly in the emerging market countries). A diversification of risk can result in less involvement in investment in the stock market.

**Table 7 Estimated Parameters of TVPMS Copula Model**

| ***Country 1*** | | | ***Germany*** | | | | | ***The UK*** | | | | | ***Poland*** | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| ***Country 2*** | ***France*** | ***The UK*** | ***Italy*** | ***Spain*** | ***Poland*** | ***France*** | ***Germany*** | ***Italy*** | ***Spain*** | ***Poland*** | ***France*** | ***Germany*** | ***The UK*** | ***Italy*** | ***Spain*** |
| $\rho_1$ | **0.963** | **0.827** | **0.913** | **0.917** | **0.748** | **0.844** | **0.828** | **0.791** | **0.793** | **0.705** | **0.748** | **0.748** | **0.718** | **0.768** | **0.732** |
| $\rho_2$ | **0.884** | **0.622** | **0.679** | **0.723** | **0.373** | **0.638** | **0.621** | **0.502** | **0.468** | **0.433** | **0.428** | **0.373** | **0.442** | **0.439** | **0.457** |
| $\beta_0^1$ | **3.051** | **3.185** | **3.723** | **3.681** | **3.008** | **3.511** | **3.196** | **3.984** | **3.977** | **4.358** | **3.034** | **3.061** | **4.105** | **2.363** | **2.760** |
| $\beta_{L_1}^1$ | -0.847 | -0.639 | -1.333 | -2.569 | -3.455 | -1.883 | -0.782 | -2.778 | -3.456 | -3.216 | 2.584 | -0.142 | 5.512 | 1.251 | 1.462 |
| $\beta_{L_2}^1$ | -0.140 | -0.686 | 1.536 | 2.182 | -0.165 | 0.126 | -0.685 | 3.198 | 2.893 | 5.732 | -1.904 | -3.383 | -2.855 | 1.630 | -0.748 |
| $\beta_{C_1}^1$ | 0.018 | 0.884 | -1.586 | -0.129 | 0.211 | 4.612 | 2.634 | 3.426 | 0.272 | 4.464 | -0.074 | -0.343 | -1.562 | -0.961 | 2.023 |
| $\beta_{C_2}^1$ | 0.597 | 2.117 | 0.899 | 3.169 | -0.365 | 3.204 | 0.596 | 0.360 | -3.157 | -2.041 | 2.716 | 0.278 | 4.674 | 1.384 | 2.188 |
| $\beta_{I_1}^1$ | -0.112 | 0.592 | -1.151 | 1.046 | 0.956 | -0.478 | -0.498 | -0.650 | 0.505 | -1.128 | 0.816 | -1.303 | -1.044 | 1.638 | -0.594 |
| $\beta_{I_2}^1$ | -0.209 | -0.416 | 0.635 | -1.166 | -1.423 | -2.022 | 0.858 | -0.891 | 0.608 | -1.226 | -0.330 | 0.866 | -0.887 | -0.716 | -1.922 |
| $\beta_{U_1}^1$ | -0.308 | -0.725 | -0.706 | -2.027 | -0.832 | -0.016 | -0.784 | -1.044 | **1.356** | -0.888 | **1.719** | **2.243** | -0.627 | **1.510** | 0.388 |
| $\beta_{U_2}^1$ | -0.006 | -0.605 | -2.474 | 1.736 | **2.210** | -2.565 | -0.776 | 0.377 | **1.517** | -0.783 | -0.228 | -0.798 | -0.838 | **3.014** | 1.748 |
| $\beta_0^2$ | **2.885** | **3.104** | **3.085** | **3.712** | **1.889** | **3.445** | **3.088** | **4.303** | **3.498** | **4.508** | **1.940** | **1.963** | **4.704** | **2.361** | **3.312** |
| $\beta_{L_1}^2$ | 0.279 | 0.660 | **1.792** | -0.755 | **1.074** | **2.129** | 1.207 | **2.754** | **1.928** | **8.446** | -0.922 | -1.134 | -1.588 | 0.025 | -1.891 |
| $\beta_{L_2}^2$ | -0.295 | 1.022 | -0.585 | -0.128 | -1.210 | **0.526** | 0.839 | **3.832** | **1.852** | -1.417 | **2.363** | **1.071** | **7.829** | **1.596** | 3.012 |
| $\beta_{C_1}^2$ | 0.597 | -0.008 | 0.635 | 1.848 | -0.363 | 0.835 | 0.353 | 0.497 | 0.504 | 1.256 | 0.103 | -0.502 | -1.106 | 0.160 | 2.460 |
| $\beta_{C_2}^2$ | -0.544 | 0.418 | -1.217 | 1.120 | -0.480 | -2.855 | 0.204 | -2.435 | -0.893 | -0.791 | 1.010 | -0.392 | 0.793 | 2.360 | 0.506 |
| $\beta_{I_1}^2$ | -0.370 | 0.627 | -0.020 | 0.770 | 1.883 | 0.237 | -0.015 | 0.133 | 0.652 | -0.571 | 1.154 | -1.951 | -0.439 | 2.439 | -0.623 |
| $\beta_{I_2}^2$ | 0.302 | 0.045 | -0.837 | -0.283 | -2.022 | 0.221 | 0.929 | -2.954 | -1.021 | -0.474 | -0.554 | 1.872 | -0.308 | -2.357 | -1.718 |
| $\beta_{U_1}^2$ | 0.107 | 0.269 | 0.032 | 1.274 | 0.406 | -0.748 | 0.477 | -1.324 | -1.168 | 1.352 | -2.928 | -2.758 | -1.577 | -3.514 | -1.653 |
| $\beta_{U_2}^2$ | 0.075 | 0.477 | 2.364 | 0.385 | -2.763 | 2.021 | 0.271 | 1.789 | 3.420 | -1.435 | 0.221 | 0.366 | 1.160 | 2.506 | -1.053 |
| LM | 6.352 | 16.167 | **25.972** | 14.953 | **39.284** | **27.523** | 17.461 | **35.027** | **28.692** | **23.983** | **24.677** | **39.220** | **23.093** | **23.626** | 16.488 |
| p-value | 0.984 | 0.441 | **0.054** | 0.528 | **0.001** | **0.036** | 0.356 | **0.004** | **0.026** | **0.089** | **0.076** | **0.001** | **0.087** | **0.098** | 0.419 |

*Notes:* The results of the TVTMP model parameters estimated by using Hamilton filtering. The significance of the model parameters was obtained via Monte Carlo simulations and was carried on only for cases where the TVPMS model is better-suited for the data than the MS model. The significant parameters are marked in **bold.**

### 3.2.3 The Interrelations Between Polish Stock Market and the Others

Relatively many variables are important for the interdependence of the Polish stock exchange with the others; in following, we present a graphical presentation of the results only for those couples in which the Polish market is one element.

**Figure 3 Returns Volatility (left panel) and Conditional Probabilities of Being in First Regime for TVPMS Model (right panel)**

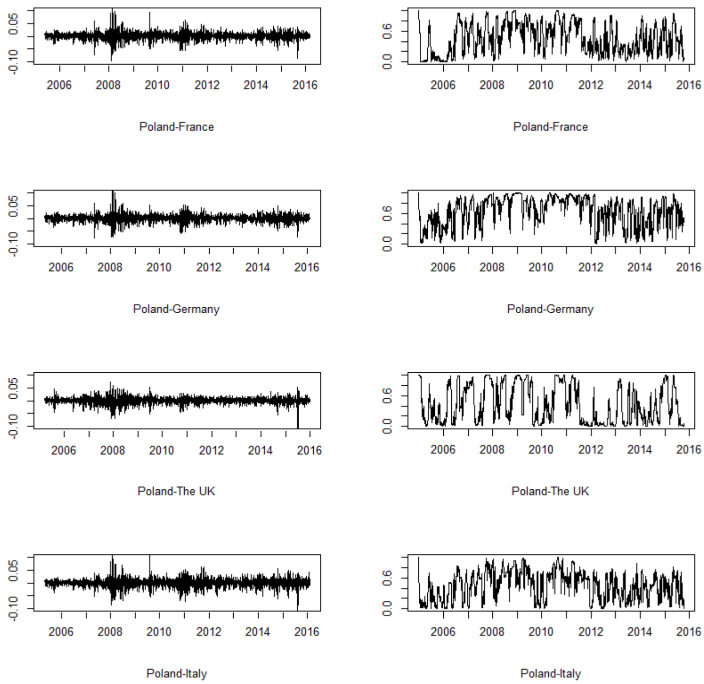


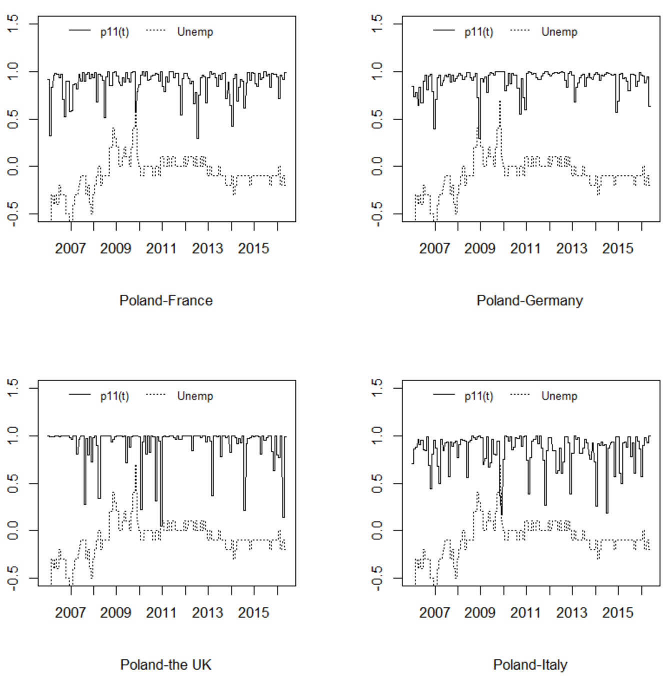

Figure 3 shows the volatility of returns (left panel) and the conditional probability of being in the first regime obtained from the TVPMS model (right panel) for the pairs of countries where the TVPMS model is better-suited for the data than the MS model; i.e., for Poland and France, Poland and Germany, Poland and the UK, and Poland and Italy. The volatility of returns has been presented for the market coming from Western European countries). From the graphs in Figure 1, it can be concluded that the high values of conditional probability indicate the periods when high volatility is observed. The financial literature suggests that strong interdependence captures periods of high return volatility driven mainly by high uncertainty in the stock market[5]. So, the states display a close link with the mood on the stocks markets. The first regime is characterized by the high volatility of returns and strong interdependence between markets. The second state relates to weaker dependence and lower volatility.

[5] Longin and Solnik (1995), Ramchand and Susmel (1998), King and Wadhwani (1990), Chesnay and Jondeau (2001), Ang and Bekaert (2002), Forbes and Chinn (2004).

The period of staying in a regime with a strong interrelationship is similar for all four pairs. The conditional probability of being in the first regime has increased since around 2007. That year was the beginning of the world financial crisis associated with the severe recession in the economy. The relatively high conditional probability of being in the first regime has also been observed since around 2008, when the volatility of returns is particularly very large. This was related to the bankruptcy of Lehman Bank. The next period, which is characterized by a high volatility of returns, is for the period of 2010-2012 (an effect of the fiscal problems in the EU). At that time, Poland's interdependence with other markets was also very strong, and the conditional probability of being in the first regime was very high. Especially for the pairing formed by the Polish and German stock exchanges, the probability of staying in the first state was high and relatively stable. After 2012, however, we can notice a weakening of the interdependencies between the markets; and over the last two years, a renewed increase in the probability of being in the first regime has occurred.

Next, Figure 4 shows the changes in the Polish unemployment rate variable compared with dynamic probabilities $p_t^{11}$ of staying in the first regime, whereas Figure 5 presents the changes in the long-term interest rates in the countries of Western Europe, with probabilities $p_t^{22}$ of staying in the second regime.

**Figure 4 Probability of Staying in First Regime (solid line) and Changes in Unemployment Rate (dotted line)**



We can notice that the increments of the unemployment rate in Poland are often associated with the increments of probabilities $p_t^{11}$. For the pairing of Poland and France, we note that the decline in Polish unemployment is reflected in decreases in the probability of staying in the regime with strong dependence until 2009. In addition, if the fluctuation of unemployment rates is small, then the probability is also stabilized. During the period of 2009-2011, we observe very small increases in the unemployment rate, so the probability fluctuations are also relatively small. After 2013, there is a clear reduction in unemployment in Poland, which is also associated with a decrease in probability value $p_t^{11}$. The same conclusion that declines in Polish unemployment is reflected in decreases in the probability of staying in first regime is obtained for the pairing of Poland and Germany. Fluctuations in unemployment and probabilities $p_t^{11}$ are more consistent than in the previous case. The obtained results of research on the mutual relationship between Poland and the British stock exchange indicate a rather-weak similarity between the change in probability $p_t^{11}$ and unemployment. Parameters $\beta_{U_1}^1$ or $\beta_{U_2}^1$ in Table 5 are also insignificant. The similarity of changes in the probability of staying in the first regime as related to changes in the unemployment rate is also observed for the pairing created by the Polish and Italian markets. However, apart from the Polish unemployment rate, the Italian unemployment rate is also important in this case for the mutual relationship of both markets.

**Figure 5 Probability of Staying in Second Regime (solid line) and Changes in Long-Term Interest Rate (dotted line)**

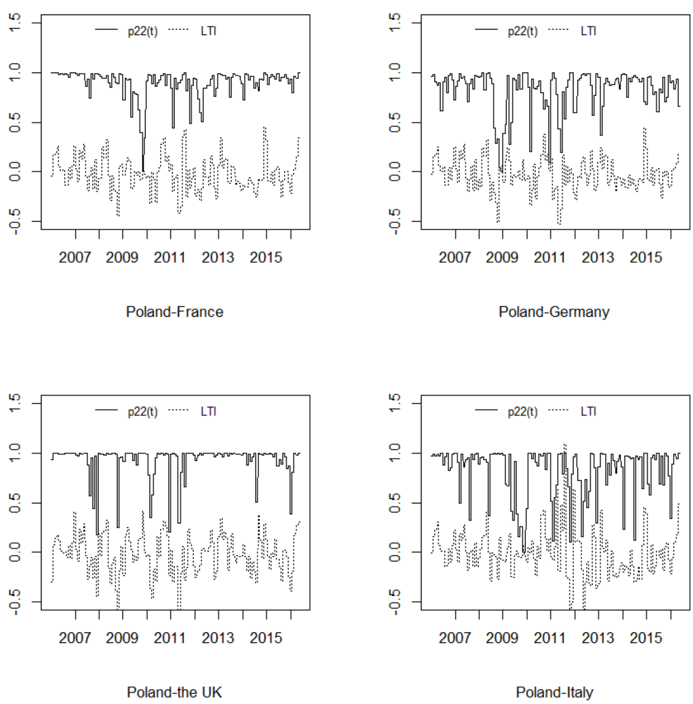


Figure 5 presents the probability of staying in the second regime and changes in the long-term interest rate. For all discussed pairs of markets, we can notice that probability $p_t^{22}$ is very strongly related to changes in the long-term interest rate.

In the case of Poland's relationship with France, this effect is poorly observed until 2008. However, the strongest similarity between the direction of the probability changes and the direction of changes in the long-term interest rate occurs after 2010. It can especially be observed that the increase in long-term interest rates is accompanied by an increase in probability $p_t^{22}$. For the case of the interrelationship between Poland and Germany, the change of probability $p_t^{22}$ is very strongly related to the change in the long-term interest rate. We note that there is a very large convergence between the fluctuations in the probability values and long-term interest rates. This effect persists throughout the whole study period. Particularly noteworthy are two sub-periods: around 2008, and again around 2011. The sharp drops in the long-term interest rate are accompanied by sharp drops in the probabilities of staying in the second regime. As related to the relationship between the Polish and British stock exchange, $p_t^{22}$ seems the most stable when compared to other relationships. Fluctuations in $p_t^{22}$ are also related to interest rate fluctuations (but slightly weaker than in previous cases). However, the probability of staying in the second regime (as in the case of Poland and Germany) also reacts to rapid drops in long-term interest rates. Therefore, we can say that, when the yield on bonds decreases, investors invest in securities on the Polish stock exchange, which translates to an increase in the interdependence of the markets. The effect of simultaneous changes in the long-term interest rate and probabilities $p_t^{22}$ is also noticeable in studying the interdependence of the Polish and Italian stock exchanges. In particular, we observed that rapid changes in long-term rates are in line with rapid changes in the probability of staying in the second regime during the period after 2010 (similar to Poland's relationship with the French stock exchange).

## 4. Conclusions

This paper studies the effects of macroeconomic variables on the interdependence of financial markets. We have verified the importance of the following macroeconomic factors: the consumer price index, industrial production rate, long-term interest rate, and unemployment rate for the strength of interrelationships between the G6 countries.

We modeled market returns by the Markov-switching copula model with time-varying probabilities for the transitions. There were two states of financial markets taken into consideration. The first is characterized by the stronger interdependence between index returns, and the second relates to the weaker interdependence. In order to check the significance of the considered macroeconomic variables in the interdependencies between markets, the TVPMS copula model was compared with the MS copula model with fixed transition probabilities.

The selection of the macroeconomic factors was done in two steps. Firstly, we tested the null hypothesis of first model against a second one. Secondly, we required some parameters of the transition probabilities: $\beta_1$, $\beta_2$ to be statistically significant.

After taking the macroeconomic variables into consideration, we noticed that the unemployment rate and long-term interest rate are of great importance for the interrelationships between the Polish stock market and the French, German, British, and Italian stock markets, respectively. The unemployment rate in Poland is associated with the probability of staying in the regime of high interdependence for the interrelationships between Poland and France, Germany, or Italy. Only for the relationship between Poland and the UK was the effect of unemployment not noted. The long-term interest rates of France, Germany, the UK, and Italy are significantly associated with the probability of staying in the regime of weak interdependence. An increase in the unemployment rate increases the probability of staying in the first regime. Changes in long-term interest rates in the G5 countries are the cause of the same direction of changes in the probability of staying in the second regime.

For a description of the relationships between developed markets, the empirical findings show that only the long-term interest rate impact the probability of staying in the second regime. This effect has been observed for the interrelationships of the German and Italian stock exchanges and for Britain and the other stock exchanges (except Germany's).

The obtained results showed that the long-term interest rate is of the highest importance among all considered macroeconomic variables. However, in the case of Poland (where the financial market is treated as an emerging market), the unemployment rate also affects the interdependence between Poland and some other markets.

# APPENDIX

**Table A1 The Estimated Parameters of TVPMS Copula Model**

| *Country 1* | *Poland* | | | | | *Germany* | | | | *The UK* |
|---|---|---|---|---|---|---|---|---|---|---|
| *Country 2* | *France* | *Germany* | *the UK* | *Italy* | *Spain* | *France* | *the UK* | *Italy* | *Spain* | *France* |
| $\rho_1$ | **0.72** | **0.71** | **0.82** | **0.74** | **0.66** | **0.94** | **0.86** | **0.91** | **0.92** | **0.88** |
| $\rho_2$ | **0.38** | **0.19** | **0.44** | **0.39** | **0.34** | **0.49** | **0.63** | **0.68** | **0.74** | **0.72** |
| $\beta_0^1$ | **3.21** | **3.07** | **1.84** | **3.04** | **3.16** | **4.27** | **3.27** | **3.76** | **3.49** | **5** |
| $\beta_{C_1}^1$ | 1.32 | 1.17 | -0.55 | 0.48 | 1.35 | -0.02 | 0.52 | 0.05 | -0.11 | 2.18 |
| $\beta_{C_2}^1$ | 3.16 | 2.25 | 0.95 | 0.46 | 1.17 | 0.45 | 0.92 | 0.82 | 0.55 | 1.91 |
| $\beta_{I_1}^1$ | 0.07 | -0.01 | -0.04 | 0.03 | 0.33 | -0.06 | -0.12 | -0.07 | -0.01 | -1.59 |
| $\beta_{I_2}^1$ | -0.14 | 0.09 | -0.02 | 0.04 | -0.14 | 0.05 | 0.3 | 0.23 | 0.32 | 1.61 |
| $\beta_{L_1}^1$ | 1.38 | -0.74 | **2.31** | 0.71 | 0.46 | 0.59 | 0.14 | 0.64 | 0.15 | 1.57 |
| $\beta_{L_2}^1$ | -1.45 | -2.53 | -0.59 | 0.69 | -0.24 | 0.81 | -0.75 | 1.35 | 0.63 | -1.9 |
| $\beta_{U_1}^1$ | **3.45** | **3.83** | **1.91** | **1.94** | 1.31 | 0.72 | 0.78 | 0.65 | 0.76 | **1.12** |
| $\beta_{U_2}^1$ | 1.34 | -0.61 | 0.83 | 1.21 | **5.41** | 1.43 | 1.97 | 0.67 | 1.96 | **3.11** |
| $\beta_0^2$ | **2.05** | **1.34** | **2.37** | **3.08** | **3.17** | **0.79** | **2.79** | **3.08** | **4.08** | **3.82** |
| $\beta_{C_1}^2$ | 0.50 | 1.1 | 0.15 | 0.81 | 0.79 | 1.45 | 0.64 | 0.95 | 1.64 | 0.3 |
| $\beta_{C_2}^2$ | 2.09 | 3.26 | 0.59 | 1.27 | 0.95 | 1.08 | 0.89 | 0.38 | 0.57 | 1.6 |
| $\beta_{I_1}^2$ | 0.08 | -0.08 | 0.02 | -0.04 | 0.53 | 0.12 | -0.11 | 0.12 | 0.02 | -0.57 |
| $\beta_{I_2}^2$ | -0.25 | 0.33 | 0.14 | 0.13 | 0.05 | -0.15 | 0.39 | 0.21 | 0.18 | 0.55 |
| $\beta_{L_1}^2$ | -0.65 | -2.47 | -0.42 | -0.28 | -1.44 | 1.14 | 1.24 | 1.29 | 1.1 | **0.69** |
| $\beta_{L_2}^2$ | **4.48** | **1.43** | **4.09** | **2.93** | **3.27** | 0.97 | 1.47 | 0.22 | 1.51 | **2.69** |
| $\beta_{U_1}^2$ | -1.16 | -1.28 | -0.96 | -0.91 | 0.23 | 0.94 | 1.03 | 0.83 | 1.04 | 0.89 |
| $\beta_{U_2}^2$ | 1.57 | 4.09 | 1.13 | 1.82 | -1.59 | 0.7 | 0.51 | 1.3 | 0.32 | -0.96 |
| LM | 26.34 | 43.60 | 25.98 | 23.80 | 30.03 | 5.84 | 12.32 | 9.14 | 10.22 | 23.82 |
| p-value | 0.05 | 0.00 | 0.05 | 0.09 | 0.02 | 0.98 | 0.72 | 0.91 | 0.86 | 0.09 |

*Notes:* The results of TVTMP model parameters estimated by using Hamilton filtering. The significance of model parameters was obtained via Monte Carlo simulations and was carried on only for cases where the TVPMS model is better suited for the data than MS model. The significant parameters are marked in **bold**.

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