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# (I)rationality of Investors on Croatian Stock Market: Explaining the Impact of American Indices on Croatian Stock Market

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***Abstract:*** American stock markets are by far the most influential markets in the world, and the abundance of information coming from them is closely monitored all over the planet. However, it seems difficult to rationally explain the immense scope of impact of the US stock indices on a rather small market such as Croatian. Zagreb Stock Exchange quotes Croatian companies that have low international significance, can rarely be perceived as strong regional players, and their connections with the USA (if any) are weak and mostly exceptions to the rule. This study follows the methodology and findings of Erjavec and Cota (2007), as an extension and further examination of the dependency of the Crobex index to the main US indices (DJIA, S&P500, NASDAQ). The econometric study is widened, and the persistent relationship between Croatian and American indices is additionally elaborated using ARIMA and GARCH models. Along with quantitative determination of the interconnectedness three concepts are introduced to explain high correlation and co-movements between Croatian and American indices; global factors, contagion and irrational escalation.

***Keywords:*** ARIMA, GARCH, Crobex, Zagreb Stock Exchange, financial crisis, behavioural finance

***JEL Classification:*** F37, G15

## Introduction

Being the world's financial leader, the impact of American Stock markets and their respective indices on other financial systems is enormous. An interdisciplinary approach, combining econometrics with behavioural finance, was used to examine and to explain the behaviour of investors on the Croatian stock market. Following the

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methodology and findings of Erjavec and Cota (2007), the dependency of the Crobex index to the main US indices (DJIA, S&P500, NASDAQ) is further examined in this paper. However, this study uses data from a different period than that of Erjavec and Cota (2007), including the data from the beginning of the World Financial Crisis followed by extreme volatility shocks. The econometric study is widened, and the persistent relationship between Croatian and American indices is additionally elaborated using ARIMA and GARCH models.

Despite the fact that intra-sectoral connections between Croatian and American business sectors are rather weak, it is clear that the investors on the Croatian stock market dominantly rely on American indices movements. This was especially apparent during the beginning of the financial crisis in October 2008 when prices of Croatian companies had almost nothing to do with their business results, which is apparent in Figure 1. It is clear that the investors on the Croatian stock market often rely more on the dealings of American companies than on corporations whose stocks they in fact own. The behaviour of Croatian investors[1] is largely based on the psychological effects of the crisis, and this is why behavioural finance is introduced to explain what pure financial reasoning could not.

It may be over-simplified, but stock markets should first and foremost be a pragmatic and impartial instrument of declaring the real price (value) of a corporation according to the successfulness of its business. If a company conducts its business outside the US markets and has no direct links or relations to the USA, as most Croatian companies do not, than a sturdy influence of American markets on the Croatian market cannot be explained using only rational reasoning. This is why behavioural finance was brought in, as it can be helpful in illuminating the features of this interconnectedness.

## Previous Studies

Only few researchers have explored the degree of integration and cross - market relations between Crobex and non-Croatian indices.

Erjavec and Cota (2007) examined the impact of European and American indices on Zagreb Stock Exchange's main index – Crobex, using GARCH models on a dataset from the period of January 4th 2000 to December 31st 2004. The estimates of the dynamic GARCH (1.1) models confirmed that one day lagged[2] movements of DJIA and NASDAQ provide signals for the direction of change of the Crobex. The positive impact of DAX30 and FTSE100 on Crobex is also confirmed, but is significantly lower, which indicates that American markets have a stronger impact on Crobex than the European markets. Bearing in mind the inter-relations between the

Croatian and European financial systems, this has to be qualified as an intriguing conclusion.

Dadić and Vizek (2006) examined the bilateral and multilateral integration of equity markets of selected Central Eastern European (CEE) countries including Croatia, and the German equity market for the period of January 2nd 1997 to June 10th 2005. Their results indicate the multilateral integration among CEE countries and between the group of CEE countries and the German equity market. Contrary to the findings of Erjavec and Cota (2007), no evidence of bilateral integration between Crobex and DAX was found.

However, relations between stock markets of the countries comparable to Croatia (namely Central- and Eastern-European countries) and American markets have been investigated, and a brief number of these studies is presented here. Gilmor and Mcmanus (2002) found that the three Central European equity markets (Hungarian, Polish, and Czech) are not cointegrated with the US market, but made it clear that the correlations of these countries with the US are increasing over time. Voronkova (2004: 645) examined connections between three emerging CE markets (the Czech Republic, Hungary, and Poland), three developed European stock markets (Britain, France, and Germany), and the United States, and found 'strong evidence in favour of significant long-run relations between the emerging CE markets within the region and globally than has previously been reported.' Černy (2004: 17) showed that stock markets in Warsaw and Prague react to the information revealed on the Frankfurt exchange after 30 minutes to 1 hour, while 'US markets seem to be important sources of information for the Frankfurt stock exchange'iv, therefore linking Polish and Czech markets to US markets.

This study expands the findings of Erjavec and Cota (2007) and strives to examine and to further explain the dynamics of the American influence on a small market such as the Croatian one, using a completely different dataset (January 3rd 2005 to November 6th 2008) and GARCH, as well as other econometric techniques.

Despite the fact that intra-sectoral connections between Croatian and American business sectors are rather weak, it is clear that the investors on the Croatian stock market dominantly rely on American indices movements. This was especially apparent during the beginning of the World Financial Crisis in October 2008 when the prices of Croatian companies had almost nothing to do with their business results. The behaviour of Croatian investors was largely based on the psychological effects of the crisis, and this is why behavioural finance is introduced to explain what pure financial reasoning could not.

Rather than just elaborating that the impact and strong influence do exist, a step forward was made in an attempt to clarify the nature of the influence of American stock markets. Behavioural finance can be helpful in elucidating what seems to be irrational reasoning of Croatian investors.

Autoregressive Integrated Moving Average (ARIMA) models are generalizations of the simple autoregressive model that use three tools for modelling the serial correlation in the disturbance:

- The first tool is the Autoregressive, or AR, term. The AR(1) model uses the first-order term, but in general, one may use additional, higher-order AR terms. Each AR term corresponds to the use of a lagged value of the residual in the forecasting equation for the unconditional residual.
- The second tool is the Integration order term. Each integration order corresponds to differencing the series being forecast[3].
- The third tool is the MA, or Moving Average term. A Moving Average forecasting model uses lagged values of the forecast error to improve the current forecast[4].

The basic version of the Ordinary Least Squares (OLS) model, the most widely used model in econometrics, applies the assumption of homoskedasticity[5]. Unlike OLS models Autoregressive Conditional Heteroskedasticity (ARCH) models embrace heteroskedasticity as informative; they treat heteroskedasticity as fundamental to the underlying process and a phenomenon that one would want to include and to model, not to correct.

ARCH models are designed to model and forecast conditional variances. The variance of the dependent variable is modelled as a function of past values of the dependent variable and independent, or exogenous variables.

The goal of these models is to provide a volatility measure that can be used in financial decision-making. This is of particular interest in financial analysis where volatility (viewed as a measure of risk) clustering can be observed.

ARCH models were introduced by Engle (1982) and generalized as GARCH (Generalized ARCH) by Bollerslev (1986) and Taylor (1986). GARCH is an ARMA version of ARCH as it allows estimated error to vary by its autoregression terms, but also by the variance estimate.

GARCH (*q, p*) models require three basic specifications:

- the first for the conditional mean equation (1);

$$y_t = \omega_1 + \alpha_1 + x_{t-1} + \varepsilon_t \quad (1)$$

- the second for the conditional variance (Eq. 2);

$$\sigma_t^2 = \omega_2 + \alpha_2 \varepsilon_{t-1}^2 + \alpha_3 \sigma_{t-1}^2 \quad (2)$$

- and finally, the third for the conditional error distribution, which is commonly one of the following: Gaussian distribution, Student's t, or Generalized Error Distribution.

The conditional variance (2) consists of three terms:

- $\omega$ - the constant;

- $\varepsilon_{t-1}^2$ - the ARCH term, or information about volatility observed from previous trading day, with *p* as the order of the autoregressive term, and

- $\sigma_{t-1}^2$ - the GARCH term, or the forecasted variance from the last trading day, with *q* as the order of the moving average term.

GARCH models have many extensions and variations, such as GARCH-M, EGARCH, PARCH, CGARCH, and, here applied, TARCH.

Threshold GARCH (TARCH or TGARCH) was introduced by Glosten, Jagannathan, and Runkle (1993), and Zakoian (1994). The generalized specification for the conditional variance is given by (3):

$$\sigma_t^2 = \omega + \sum_{j=1}^{q} \beta_j \sigma_{t-j}^2 + \sum_{i=1}^{p} \alpha_i \varepsilon_{t-1}^2 + \sum_{k=1}^{r} \gamma_k I_{t-k}^{-} \varepsilon_{t-k}^2 \qquad (3)$$

where $I_t^-$ is a threshold term which is a dummy variable equal to one if $\varepsilon_{t-1} < 0$ and zero otherwise.

In TARCH (3) good news ($\varepsilon_{t-i} > 0$) and bad news ($\varepsilon_{t-i} < 0$) have different effects on the conditional variance. Good news has an impact of $\alpha_i$, while bad news has an impact of $\alpha_i + \gamma_i$. If $\gamma_i > 0$, bad news increases volatility, it is said that there is a leverage effect for the *i*-th order. If $\gamma \neq 0$, the news impact is asymmetric. Therefore, GARCH is a special case of TARCH where the threshold term is set to zero and where all news equally and symmetrically influence volatility.

These models are extensively used in various branches of econometrics, especially in financial time series analysis, and they are already broadly implemented throughout the world. However, GARCH models in Croatia are not widely utilized, mostly due to unavailability of the data, and to the (generally) low level of education in econometrics among the financial practitioners.

In this study GARCH and TARCH were used largely because of the appropriateness and availability of the market data, as both Croatian and American data were rather easy to access and to examine. Furthermore, they are widely used in different studies, and their efficiency and utility is already proven.

### Behavioural Finance

Why do investors on small transition financial markets often behave in the same direction and make similar decisions like those on the main world markets? The literature on behavioural finance offers the psychologically based explanation of irrational behaviour on financial markets.

Gosh and Ray (1997) notice that individual values are often under the great influence of the group behaviour. This is comparable to the behaviour of animals, and so called 'herding' behaviour. Rubatelli (2006: 22) advocates the thesis that people adopt this kind of behaviour when they are exposed to the opinions of other individuals. 'People acting coherently with the group may appear as rational since they seem to integrate information provided by other people to their beliefs; however, it actually leads to an irrational behaviour at the group level. Paradoxically, following the same behaviour of the group could induce people to imitate each other and to give their preference to an alternative which is not the best but simply that chosen by the majority of the group members'viii. The cause of investors' irrationality Tuckett and Taffler (2008) find in the conflict between emotion (wishful thinking) and normal asset valuation. The conflict grows when the growing divergence between wishes and reality based valuation, which causes anxiety. In order to avoid anxiety investors ignore reality and become euphoric.

*The Impact of American Indices on CROBEX: Pure Logic or Something Else*

This section aims to explain causes of co-movements between S&P500 index and Crobex. In order to achieve this, the international experience has to be revised. The majority of previous studies attempted to explain the interdependence of major American, European and Japanese indices.

Karolyli and Stulz (2002) consider the problem of co-movements to be grounded in global components and the changes in correlations and spillovers reflect innovations in these common components. Under this view, spillovers show that markets incorporate information efficiently.

Similarly, Lu & Mouroukotas (1997) found psychology to be the most important factor in explaining the day-to-day performance of financial markets. The Wall Street crash and the day after the sell off in Tokyo in October 1987 is a good example of what is known as 'efficient market hypothesis', and is supposed to be an important explanation of short-term market movements.

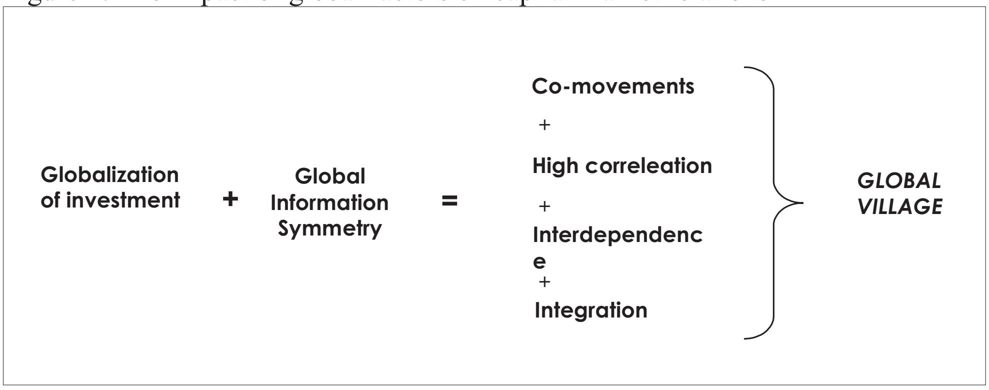
On the contrary, by applying the technique of recursive cointegration analysis Yang et al. (2004) find no long-run relationship between the researched stock markets.

The existence of an efficient market caused by almost perfect global information symmetry can be identified as one of the main reasons for co-movements in market indices, strong interdependence and global integration in the short term which are advocated by a number of authors; some of them are presented here.

Using VAR in modelling daily stock market returns Friedman & Shachmurove (1997) found the large stock markets (the United Kingdom, France, Germany and the

Netherlands) to be highly correlated. Černy (2004) identifies the US markets as an important source of information for the main European markets. London and Frankfurt stock indices react to new information within 30 minutes, with the first reaction occurring in just five minutes. Morrana & Beltrati (2008) found evidence of strong linkages across markets over the period 1973-2004, as measured by co-movements in prices and returns and in volatility processes. They found that the linkages across markets have in general, grown stronger over time, particularly for the US and Europe. The impact of global factors on capital markets can be detected through several channels (see Figure 1).

Figure 1: The impact of global factors on capital market relations




Source: authors

Although no direct co-movements and correlations between American and Croatian indices would be expected, their existence could be explained by the existence of efficient markets. This can be interpreted as additional evidence to the presence of the 'global financial village'.

The second source of co-movements and correlations is found in the contagion. This phenomena is generally defined as 'the spread of market disturbances – mostly on the downside – from one (emerging market) country to another…' (see Karoyli and Stulz (2002), even though some authors insist on more composite definitions (see Bialkowski et al., 2006). The possibility of contagion develops with the improvement of international economic relations and the increasing number of international investors. The best example of contagion is the latest US financial crisis which spread to other capital markets very quickly. The downward trend of Crobex was evident, although the Croatian economy didn't offer an economic background for this collapse.

This brings us to find the third possible cause of co-movements in behavioral finance; the term *irrational escalation* is frequently used in psychology and economics to refer to situation in which people make irrational decisions based upon rational decisions in the past or to justify actions already taken. Irrational escalation perfectly explains the bear orientation of Croatian investors after the beginning of the crisis. Without domestic economic disturbances, Croatian investors reacted completely irrationally, their behavior dependent on the news coming from the US. Another way of explaining the co movements is the herd behavior, mentioned in the previous section.

*Data*

Information sources for the indices were Yahoo Finance and Zagreb Stock Exchange websites. Corrections were done for non-mutual national holidays (i.e. non-working days); only common parallel workdays were included. Dataset has 935 observations from January 3rd 2005, to November 6th 2008. This particular dataset was used because it begins where the dataset of Erjavec and Cota (2007) ends, and the final date was the most recent at the time this paper was being prepared.

Therefore, an attempt was made to move forward from the previous studies, including also the data from the beginning of the financial crisis which clearly indicates reliance of Croatian investors on American reasoning during the times of unexpected events and crisis. Similarly as to the Engle's (1982) intentions with the ARCH and the OLS model (including heteroskedasticity, not correcting it), instead of trying to avoid this kind of possibly idiosyncratic data, this period was used with intent to additionally elaborate the confidence of Croatian investors in analysis and logic of the American investors. Choosing some other dataset may yield different results[6], but we leave this to future investigations and studies.

*Results*

Since previous studies have shown predominance of American indices over European indices in influence on the Croatian stock market, European indices were excluded from this research. Due to the difference in time zones between Croatia to New York, and consequently the non-corresponding working hours, the impact of American indices is lagged one day.

It was assumed that the raw index data was non-stationary, and the Augmented Dickey-Fuller unit root test was used to examine this assumption (presented in Table 1). High-level probabilities of unit roots were found with all indices in data level, but first differencing satisfied the condition of stationarity.

Table 1: Augmented Dickey-Fuller test statistics

| $H_0$: Index has a unit root | | | | |
|---|---|---|---|---|
| Index | Data level | | 1st difference | |
| | t-Statistic | Prob.* | t-Statistic | Prob.* |
| Crobex | -1,173 | 0,688 | -26,429 | 0,000 |
| DJIA | -0,517 | 0,885 | -24,807 | 0,000 |
| NASDAQ | -0,946 | 0,773 | -24,384 | 0,000 |
| S&P500 | 0,016 | 0,958 | -25,393 | 0,000 |

*MacKinnon (1996) one-sided p-values.

The Matrix of correlations between variables, as presented in Table 2 (probability levels are given in parenthesis), indicate possible multicollinearity issues. Therefore, it was decided to use only the Standard&Poor's 500 index, which is wider than the Dow Jones Industrial Average, and contains corporations that are traded both on NASDAQ and NYSE. Hence, S&P500 is used as the key representative American index.

In order to examine serial correlations, corellogram of residuals ($u_t$) was examined for the equation

$$\log r_t^{Crobex} = c_1 + c_2 \log r_{t-1}^{Crobex} + c_3 \log r_{t-1}^{S\&P\,500} + u_t \qquad (4)$$

which yielded significant Q-statistics from lag three onwards. The results are presented in Table 3.

Table 2: Correlation matrix for selected indices

| | DJIA | S&P500 | NASDAQ | Crobex |
|---|---|---|---|---|
| DJIA | 1,000 | | | |
| | (-) | | | |
| S&P500 | 0,971 | 1,000 | | |
| | (0,00) | (-) | | |
| NASDAQ | 0,944 | 0,961 | 1,000 | |
| | (0,00) | (0,00) | (-) | |
| Crobex | 0,909 | 0,826 | 0,821 | 1,000 |
| | (0,00) | (0,00) | (0,00) | (-) |

Seven lags (Table 3) were chosen as it is assumed that investors and financial experts react promptly and immediately to new information, and that these new information are incorporated very swiftly into their actions on the market. Financial experts are generally well informed and keep themselves up-to-date with current news; therefore it is very unlikely for them to have delayed reactions of over one week. Hence, including further lags was perceived as unnecessary.

Table 3: Ljung Box Q-statistics for Crobex serial correlations

| Lag | Q-Stat | Prob. |
|---|---|---|
| 1 | 0,0016 | 0,968 |
| 2 | 0,0081 | 0,996 |
| 3 | 15,108 | 0,002 |
| 4 | 18,361 | 0,001 |
| 5 | 30,391 | 0,000 |
| 6 | 30,469 | 0,000 |
| 7 | 31,193 | 0,000 |

A structural regression model was described, and AR terms with lags three and five were chosen after careful examination of Schwartz information criterion for various models[7]. Therefore, the model considered is

$$\log r_t^{Crobex} = \omega_1 + \alpha_1 \log r_{t-1}^{S\&P\,500} + u_t \tag{5}$$

where

$$u_t = \alpha_2 u_{t-3} + \alpha_3 u_{t-5} + \varepsilon_t \tag{6}$$

with the variance equation specified as

$$\sigma_t^2 = \omega_2 + \alpha_4 \varepsilon_{t-1}^2 + \alpha_5 \sigma_{t-1}^2 \tag{7}$$

Three and five day lags could be explained with the impact of investment funds on the Croatian markets. A large contraction in the Croatian investment funds industry occurred in the period examined, contrary to its boom in previous years, and many investors withdrew their stakes during the beginnings of the World Financial Crisis. They reacted to the market signals, and investment funds were forced to sell their assets to pay off the investors. Since it takes few days for the funds to execute the payment orders, this was reflected in the residuals and their serial correlation.

This provided the ARIMA (3,1,0) model as presented in Table 4. The constant was found insignificant, and the impact of S&P500 is relatively strong. Auto-regressions from three- and five-day lags are similar in strength.

Table 4: ARIMA (3,1,0) model

| Variable | Coefficient | Prob. |
|---|---|---|
| C | 0,000 | 0.5615 |
| First difference of one-day lagged log S&P500 | 0,378 | 0.0000 |
| AR(3) | 0,140 | 0.0000 |
| AR(5) | 0,143 | 0.0000 |
| R-squared | 0,119 | |
| Adjusted R-squared | 0,116 | |
| F-statistic (p-level) | 41,64 (0,00) | |
| SIC | -5,616 | |

The residuals from the specified ARIMA (3,1,0) model are nearly white noise and no considerable serial correlations are left in the residuals (Table 5).

Different specifications for the mean equation of the GARCH model were examined, and the models were named A to F. The mean equation is specified as in the (5) and (6), and in the models D, E and F the auto-regression terms were excluded.

Table 5: Ljung-Box Q statistics for ARIMA (3,1,0) model

| Lag | Q-Stat | Prob. |
|---|---|---|
| 1 | 0,0116 | |
| 2 | 0,1304 | |
| 3 | 0,3421 | 0,559 |
| 4 | 3,7534 | 0,153 |
| 5 | 5,3598 | 0,147 |
| 6 | 6,3993 | 0,171 |
| 7 | 7,5060 | 0,186 |

Three designs were observed: GARCH (1,0), (0,1), and (1,1). No variance regressors were specified in this study, and error distribution was assumed to be normal.

Table 6: ARCH(7) LM test for models A to F

| | | | |
|---|---|---|---|
| A | F-statistic | 0,444 | (0,874) |
| | Obs*$R^2$ | 3,126 | (0,873) |
| B | F-statistic | 0,437 | (0,879) |
| | Obs*$R^2$ | 3,079 | (0,878) |
| C | F-statistic | 0,406 | (0,898) |
| | Obs*$R^2$ | 2,860 | (0,898) |
| D | F-statistic | 0,333 | (0,939) |
| | Obs*$R^2$ | 2,346 | (0,938) |
| E | F-statistic | 3,121 | (0,003) |
| | Obs*$R^2$ | 21,529 | (0,003) |
| F | F-statistic | 36,064 | (0,000) |
| | Obs*$R^2$ | 199,724 | (0,000) |

The Lagrange Multiplier Test was conducted for all models, A to F, in order to inspect whether there are any ARCH effects in the residuals. The testing was done up to ARCH(7) effect, as shown in Table 6 (p-levels are given in parenthesis). The null hypothesis stating there is no ARCH up to order 7 in the residuals was accepted for models A, B, C, and D. Models GARCH(1,0) and (0,1) named E and F showed existing ARCH effects in the residuals after order 7.

The results of GARCH models with the above specifications are presented in Table 7 (p-levels are given in parenthesis, under coefficients).

Model D yields the best results: with no ARMA terms and GARCH (1,1) specification it shows a relatively strong impact of S&P500 index on Crobex.

The results for the Dow Jones Industrial and NASDAQ indices are similar to the S&P500, which was an expected result after observing very high correlations between them (as presented in Table 2). Therefore, they are not presented here.

An experiment with GARCH-in-Mean (GARCH-M) design which introduced variance in the mean equation in model D did not improve that model; the $\sigma^2$ in mean with z-statistics at –0.74 was found to be statistically insignificant (p-level = 0.4569).

Table 7: GARCH models results

| Dependant variable: First difference of log Crobex | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| Model name | Mean equation | | | | Variance equation | | | Schwarz criterion |
| | Const. $\omega_1$ | First difference of one day lagged log S&P500 $\alpha_1$ | AR(3) $\alpha_2$ | AR(5) $\alpha_3$ | Const. $\omega_2$ | $\varepsilon^2_{t-1}$ $\alpha_4$ | $\sigma^2_{t-1}$ $\alpha_5$ | |
| A | 0,001 | 0,185 | 0,035 | 0,068 | 0,000 | 0,148 | 0,815 | -6,064 |
| | (0,010) | (0,000) | (0,297) | (0,079) | (0,000) | (0,000) | (0,000) | |
| B | 0,001 | 0,187 | 0,044 | - | 0,000 | 0,142 | 0,826 | -6,066 |
| | (0,005) | (0,000) | (0,186) | - | (0,000) | (0,000) | (0,000) | |
| C | 0,001 | 0,185 | - | 0,072 | 0,000 | 0,156 | 0,804 | -6,070 |
| | (0,008) | (0,000) | - | (0,057) | (0,000) | (0,000) | (0,000) | |
| D | 0,001 | 0,185 | - | - | 0,000 | 0,170 | 0,788 | -6,072 |
| | (0,003) | (0,000) | - | - | (0,000) | (0,000) | (0,000) | |
| E | 0,001 | 0,072 | - | - | 0,000 | 0,674 | - | -5,959 |
| | (0,015) | (0,000) | - | - | (0,000) | (0,000) | - | |
| F | 0,000 | 0,336 | - | - | 0,000 | - | 0,719 | -5,580 |
| | (0,347) | (0,000) | - | - | (0,803) | - | (0,000) | |

Table 8: TARCH estimation output

| Model name:T Schwarz criterion:-6,071 | Mean equation | | | | |
|---|---|---|---|---|---|
| | | Const. $\omega_1$ | First difference of one day lagged log S&P500 $\alpha_1$ | | |
| | Coeff. | 0,000 | 0,177 | | |
| | | (0,185) | (0,000) | | |
| | Variance equation | | | | |
| | | Const. $\omega_2$ | $\varepsilon^2_{t-1}$ $\alpha_2$ | $\varepsilon^2_{t-1}(\varepsilon_{t-1} < 0)$ $\alpha_3$ | $\sigma^2_{t-1}$ $\alpha_4$ |
| | Coeff. | 0,000 | 0,101 | 0,086 | 0,813 |
| | | (0,000) | (0,000) | (0,001) | (0,000) |

Additionally, TARCH specification was also introduced in order to examine if it would improve the model D. TARCH has a desirable property – it can model the different effect of bad news ($\varepsilon_{t-1} < 0$) and good news ($\varepsilon_{t-1} > 0$) on the conditional variance, and it provides a solution for the larger impact of bad news on the volatility. The results are given in Table 8.

However, modelling above explained differential impact did not significantly improve the results, which further confirms the basic statement that Croatian investors often simply follow the information coming from US markets without profound insight of the underlying nature of these information.

## Conclusion

This paper uses GARCH and TARCH models to examine impact of the US markets indices on Croatian stock market index (Crobex). In the short run, psychological factors were found to play an important role in determining Croatian stock market movements.

Despite the fact that direct relationships between Croatian and American business sectors are rather weak, it is clear that the investors on the Croatian stock market dominantly rely on American indices movements.

Examining the strength of the impact of American indices on the Croatian stock market index (Crobex) we chose a single stock market index, S&P500, as a key representative American index, and found relatively firm connection between S&P500 and Crobex.

Since S&P500 is highly correlated with DJIA and NASDAQ, similar results were obtained with those indices as well.

High correlation and co-movements between Croatian and American indices could be explained by four concepts; global factors, contagion, irrational escalation and herd behavior at financial markets. The first two factors are interrelated, and not possible to analyze separately. It is expected that their impact on global equity markets will grow in the upcoming years which will encourage further integration of capital markets.

## NOTES

[1] One could argue if they were investors at all, since their demeanour resembles more to those of outright speculators.

[2] Primarily as a consequence of different time zones.

[3] A first-order integrated component means that the forecasting model is designed for the first difference of the original series; a second- order component corresponds to using second differences, and so on.

[4] A first-order moving average term uses the most recent forecast error, a second-order term uses the forecast error from the two most recent periods, and so on.

[5] OLS assumes that the expected values of all error terms are the same at any given point. Hence, the expected value of any given error term squared is equal to the variance of all the error terms taken together. On the contrary, data for which the error terms may be expected to be larger for some points or ranges of the data than for others suffers from heteroskedasticity.

[6] We believe that this study, together with previous ones, has proved what regional financial experts have in practice already determined: the confidence and the reliance of Croatian investors to reasoning of American investors; furthermore – pricing Croatian companies on the stock market not primarily according to their fundamentals, but rather to the perception and expectation of investors in the US markets. Therefore we believe that choosing different datasets would not yield fundamentally different results, rather just differences in scopes of the results.

[7] Full results are available from the authors upon request.

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## Appendix

Figure 2: Daily returns of S&P500 and Crobex during the beginning of the World Financial Crisis