

# An empirical analysis on volatility: Evidence for the Budapest stock exchange using GARCH model

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## **Abstract:**

**T**he paper aims to analyze and forecast the Budapest Stock Exchange volatility with the use of generalized autoregressive conditional heteroscedasticity GARCH-type models over the time period from September 06, 2010 to March 03, 2017. This model is the extension of ARCH process with various features to explain the obvious characteristics of financial time series such as asymmetric and leverage effect. As we apply the Budapest Stock Exchange with this model, the estimation and forecast in short term are performed.

**Keywords:** *Volatility, GARCH, BUX, Volatility forecast.*

## **1. Introduction**

In recent years, the study of the volatility of a market variable measuring uncertainty about the future value of the variable plays a prominent part in monitoring and assessing potential losses. Quantitative methods measure the volatility of the Budapest Stock Exchange BUX received the high interest because of its role in determining the price of securities and risk management. Typically, a series of financial indices have different movements under certain period. This means that the variance of the range of financial indicators changes over time. The Budapest Stock Exchange is one of the most crucial markets by market capitalization and liquidity in central Europe. BUX accounts for all the turnover in Hungarian market and a large share of the Central and Easter Europe market.

According to Bank (2015), the fundamental economic role of the Budapest Stock Exchange is to provide the domestic enterprises with an opportunity to raise capital. In recent years, the domestic capital market has fulfilled this role. At present, the demand side of the stock exchange is dominated by non-resident institutions. Therefore,

the investigation of the volatility of the Budapest Stock Exchange is in need.

As Bantwa (2017) mentioned, for most investors, the prevailing market turmoil and lack of clarity on where it's headed are a cause for concern. The majority of investors in markets are mainly concerned about the uncertainty in getting the expected returns as well as the volatility in returns. Andersen T. and Labys (2003) provided a framework for integrating high-frequency intraday data into the measurement, modelling, and forecasting of daily and lower frequency return volatilities and return distributions. Use of realized volatility computed from high-frequency intraday returns permits used of traditional time series methods for modelling and calculating.

Ashok and Ritesh (2011) center on comparing the performance of conditional volatility model GARCH and Volatility Index in predicting underlying volatility of the NIFTY 50 index. Using high-frequency data the underlying volatility of NIFTY50 index is captured. Several approaches to predicting realized volatility are considered.

Chatayan Wiphatthanananthakul (2010) estimated ARMA-GARCH, EGARCH, GJR and PGARCH models for Thailand Volatility Index (TVIX), and made comparison and forecast between the models. GARCH model has become key tools in the analysis of time series data, particularly in financial applications. This model is especially useful when the goal of the study is to analyse and forecast volatility. Degiannakis (2004). With the generation of GARCH models, it is able to reproduce another very vital stylized fact, which is volatility clustering; that is, big shocks are followed by big shocks.

In this paper, we applied GARCH model to estimate, compute and forecast the Budapest Stock Exchange volatility. Nevertheless, it should be pointed out that several empirical studies have already examined the impact of asymmetries on the performance of GARCH models. The recent survey by Poon and Granger (2003) provides, among other things, an interesting and extensive synopsis of them. Indeed, different conclusions have been drawn from these studies. The rest of the paper proceeds as follows: the concept of volatility and GARCH model are given in next section, the final section is discussed results and conclusion.

## 2. Theoretical Background, Concept and Definitions

### • Definition and Concept of Volatility

The volatility  $\sigma$  of a variable is defined as the standard deviation of the return provided by the variable per unit of time when the return is expressed using continuous compounding. When volatility is used for option pricing, the unit of time is usually one year, so that volatility is the standard deviation of the continuously compounded return per year. However, when volatility is used for risk management, the unit of time is usually one day, so that volatility is the standard deviation of the continuously compounded return per day.

In general,  $\sigma\sqrt{T}$  is equal to the standard deviation of  $\ln\left(\frac{S_T}{S_0}\right)$  where  $S_T$  is the value of the market variable at time T and  $S_0$  is its value today. The

expression  $\ln\left(\frac{S_T}{S_0}\right)$  equals the total return earned in time T expressed with continuous compounding. If  $\sigma$  is per day, T is measured in days, if  $\sigma$  is per year, T is measured in years, according to C.Hull (2015).

The volatility of EUR/HUF variable is estimated using historical data. The returns of EUR/HUF at time t are calculated as follows:

$$R_i = \ln \frac{p_i}{p_{i-1}}, i = \overline{1, n}$$

where  $p_i$  and  $p_{i-1}$  are the prices of EUR/HUF at time t and t-1, respectively. The usual estimates s of the standard deviation of the  $R_i$  is given by

$$s = \sqrt{\frac{1}{n-1} \sum_{i=1}^n (R_i - \bar{R})^2}$$

where  $\bar{R}$  is the mean of the  $R_i$ .

As explained above, the standard deviation of the  $R_i$  is  $\sigma\sqrt{T}$  where  $\sigma$  is the volatility of the EUR/HUF.

The variable s is, therefore, an estimate of  $\sigma\sqrt{T}$ . It follows that  $\sigma$  itself can be estimated as  $\hat{\sigma}$ , where

$$\hat{\sigma} = \frac{s}{\sqrt{T}}$$

The standard error of this estimate can be shown to be approximate  $\frac{\hat{\sigma}}{\sqrt{2n}}$ . T is measured in days, the volatility that is calculated is a daily volatility.

### • GARCH Model

GARCH model by Bollerslev (1986) imposes important limitations, not to capture a positive or negative sign of  $u_t$ , which both positive and

negative shocks have the same impact on the conditional variance,  $h_t$ , as follows

$$u_t = \eta_t \sqrt{\sigma_t}$$

$$\sigma_t^2 = \omega + \sum_{i=1}^p \alpha_i u_{t-i}^2 + \sum_{j=1}^q \beta_j \sigma_{t-j}^2$$

where  $\omega > 0$ ,  $\alpha_i \geq 0$ , for  $i = \overline{1, p}$  and  $\beta_j \geq 0$  for  $j = \overline{1, q}$  are sufficient to ensure that the conditional variance,  $\sigma_t$  is nonnegative.

For the GARCH process to be defined, it is required that  $\omega > 0$ . Additionally, a univariate GARCH(1,1) model is known as ARCH( $\infty$ ) model Engle, (1982) as an infinite expansion in  $u_{t-1}^2$ . The  $\alpha$  represents the ARCH effect and  $\beta$  represents the GARCH effect. GARCH(1,1) model,  $\sigma_t^2$  is calculated from a long run average variance rate,  $V_L$ , as well as from  $\sigma_{t-1}$  and  $u_{t-1}$ . The equation for GARCH(1,1) is

$$\sigma_t^2 = \gamma V_L + \alpha u_{t-1}^2 + \beta \sigma_{t-1}^2$$

where  $\gamma$  is the weight assigned to  $V_L$ ,  $\alpha$  is the weight assigned to  $u_{t-1}^2$  and  $\beta$  is the weight assigned to  $\sigma_{t-1}^2$ . Since the weight must sum to one, we have

$$\gamma + \alpha + \beta = 1$$

- **Volatility forecasting**

There is a vast and relatively new literature that attempts to compare the accuracies of various models for producing out-of-sample volatility forecasts. Akgiray (1989), for example, finds the GARCH model superior to ARCH, exponentially weighted moving average and historical mean models for forecasting monthly US stock index volatility.

A similar result concerning the apparent superiority of GARCH is observed by West and Cho (1995) using one-step-ahead forecasts of dollar exchange rate volatility, although for longer horizons, the model behaves no better than their alternatives.

A particularly clear example of the style and content of this class of research is given by Day and Lewis (1992). The Day and Lewis study will therefore now be examined in depth. The purpose of their paper is to consider the out-of-sample forecasting performance of GARCH and EGARCH models for predicting stock index volatility.

Arowolo, W.B employed the properties of linear GARCH model for daily closing stocks prices of Zenith bank PIC in Nigeria stocks Exchange, they concluded that the Optimal values of p and q GARCH (p,q) model depends on location, the types of the data and model order selected techniques being used. The models that Day and Lewis employ so called a ‘plain vanilla’ GARCH(1,1):

$$h_t = \alpha_0 + \alpha_1 u_{t-1}^2 + \beta_1 h_{t-1}$$

- **Data Description**

The data for our empirical investigation consists of the Budapest Stock Exchange index transaction prices that is obtained from Bloomberg, accounted by the Department of Finance, Corvinus University of Budapest, the sample period is from September 06, 2010 to March 03, 2017 which constitutes a total of n = 1694 trading days. For the estimation, we use the daily returns of Budapest Stock Exchange index to estimate GARCH(1,1) by using Eview 7.0 software.

### 3. Results and discussion

- **Descriptive Statistics**

The descriptive statistics of daily logarithmic returns of the Budapest Stock Exchange index is given in Table 1.

Table 1. Descriptive statistics of EUR/HUF Returns

Mean	Std. Dev	Skewness	Kurtosis	Max	Min
0.000251	0.012509	-0.207632	5.808442	0.055149	-0.069842
Jarque-Bera			568.8871		
Probability			0.000000		

Source: Author's calculation

The average return of BUX is positive. A variable has a normal distribution if its skewness statistic equals to zero and kurtosis statistic is 3, but the return of BUX has negative skewness statistic and high kurtosis, suggesting the presence of fat tails and a non-symmetric series. Additionally, as we can see from Jarque-Bera normality test rejects the null hypothesis of normality for the sample, this means we can draw a conclusion that the return of BUX is not normally distributed. The relatively large kurtosis indicates non-normality that the distribution of returns is leptokurtic.

Figure 1 depicts the histogram of daily logarithmic return for BUX. From this histogram, it appears that BUX returns have high peak than the normal distribution. In general, Q-Q plot is used to identify the distribution of the sample in the study, it compares the distribution with the normal distribution and indicates that BUX returns deviate from the normal distribution.

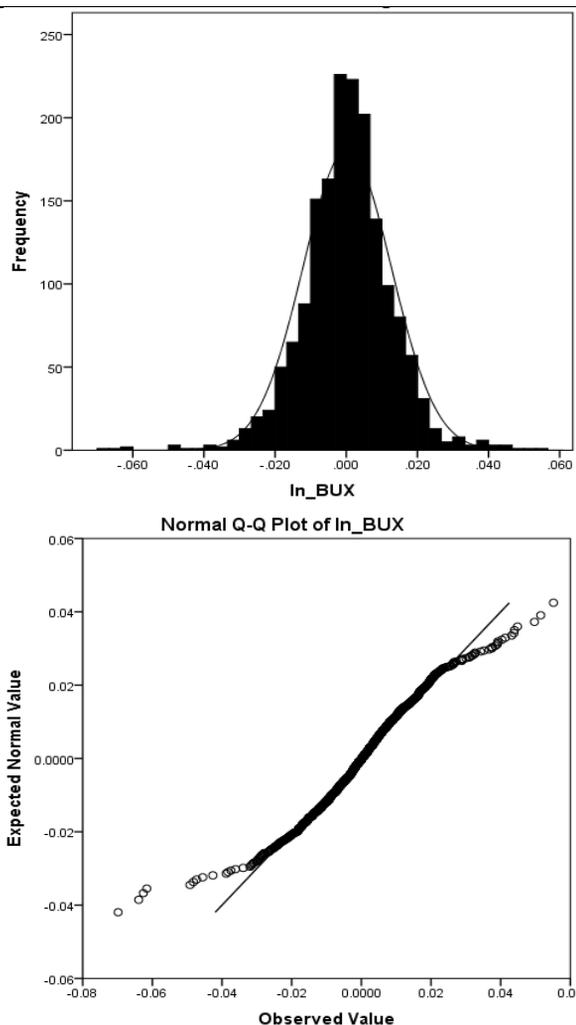
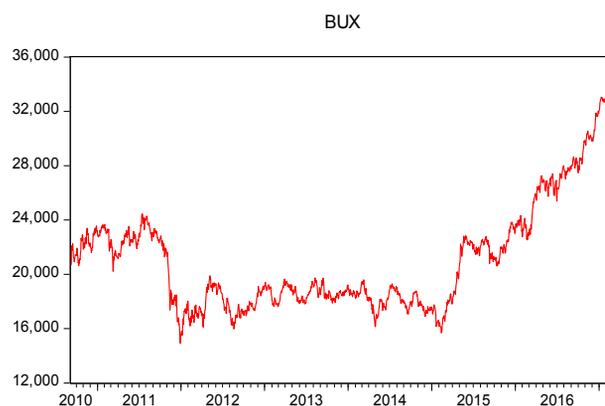


Figure 1. Histogram and Q-Q Plot of Daily Logarithmic BUX returns



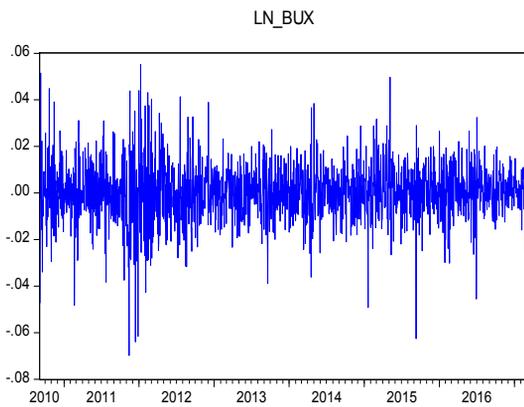


Figure 2. Daily price and BUX returns

Figure 2 presents the plot of price and BUX returns. This indicates some circumstances where BUX returns fluctuate.

Table 2. Unit root test for Returns of EUR/HUF

Test	None	Constant	Const & Trend
Phillips-Perron	-40.95554	-40.96258	-41.02295
ADF	-40.92542	-40.93358	-40.98122

Source: Author's calculation

• **Estimation**

Table 3 represents the ARCH and GARCH effects from statistically significant at 1 percent level of  $\alpha$  and  $\beta$ . It shows that the long-run coefficients are all statistically significant in the variance equation. The coefficient of  $\alpha$  appears to show the

presence of volatility clustering in the models. Conditional volatility for the models tends to rise (fall) when the absolute value of the standardized residuals is larger (smaller). The coefficients of  $\beta$  (a determinant of the degree of persistence) for all models are less than 1 showing persistent volatility.

Table 3. GARCH on Returns of BUX

GARCH					
Mean Equation			Variance Equation		
	Coefficient	z-statistics		Coefficient	z-statistics
Constant	0.000518	1.885713	$\omega$	0.0000064	5.277486 (0.0000)
Mean			$\alpha$	0.086160	7.033843 (0.0000)
			$\beta$	0.871707	50.44310 (0.0000)

Source: Author's calculation

GARCH (1,1) model is estimated from daily data as follows

$$\sigma_t^2 = 0.0000064 + 0.086160u_{t-1}^2 + 0.871707\sigma_{t-1}^2$$

Since  $\gamma = 1 - \alpha - \beta$ , it follows that  $\gamma = 0,042133$

and, since  $\omega = \gamma V_L$ . We have  $V_L = 0,000159$ . In

other words, the long run average variance per day implied by the model is 0,000159. This corresponds to a volatility of

$$\sqrt{0,000159} = 0.0123 \text{ or } 1.23 \%, \text{ per day.}$$

• **Forecasting Results Using GARCH (1,1) Model**

The selected model

$$\sigma_t^2 = 0.0000064 + 0.086160u_{t-1}^2 + 0.871707\sigma_{t-1}^2$$

has been tested for diagnostic checking and there is no doubt of its accuracy for forecasting based on residual tests. We can use our model to predict the future volatility value. Figures 3 and 4 show the forecast value. It is seen that the forecasts of the conditional variance indicate a gradual increase in the volatility of the stock returns. The dynamic forecasts show a completely flat forecast structure for the mean, while at the end of the in-sample estimation period, the value of the conditional variance was at a historically low level relative to its unconditional average. Therefore, the forecast converges upon their long term mean value from below as the forecast horizon increases. Notice also that there are no  $\pm 2$ -standard error band confidence intervals for the conditional variance forecasts. It is evidence for, static forecasts that the variance forecasts gradually go up the out-of-sample period, they show much more volatility than for the dynamic forecasts.

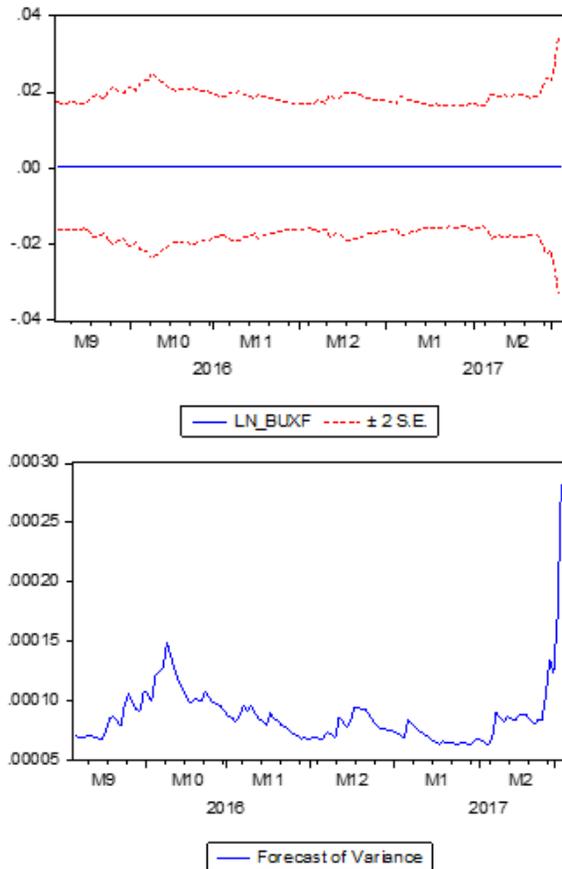


Figure 3. Static forecasts of the conditional variance

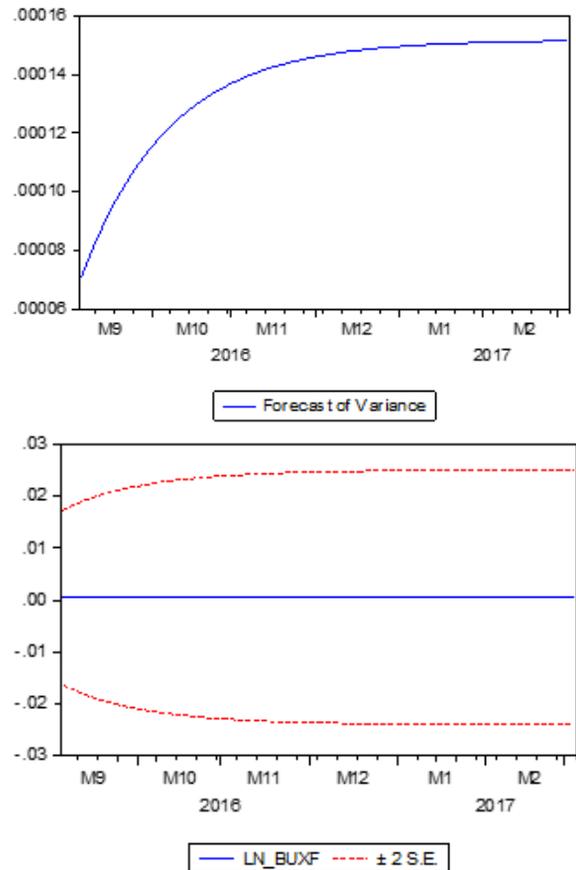


Figure 4. Dynamic forecasts of the conditional variance

## Conclusions

This paper estimates the volatility of the Budapest Stock Exchange returns using GARCH model from the seemingly complicated volatility formula established by Bollerslev (1986). The results of statistical properties obtained supported the claim that the financial data are leptokurtic. The GARCH model was identified to be the most appropriate for the time-varying volatility of the data. The results from an empirical analysis based on the Budapest Stock Exchange showed the volatility is 1.23 % per day. Additionally, the results of forecasting conditional variance indicate a gradual increase in the volatility of the stock returns. This is in contrast to the work of Chatayan Wiphatthananthakul (2010).

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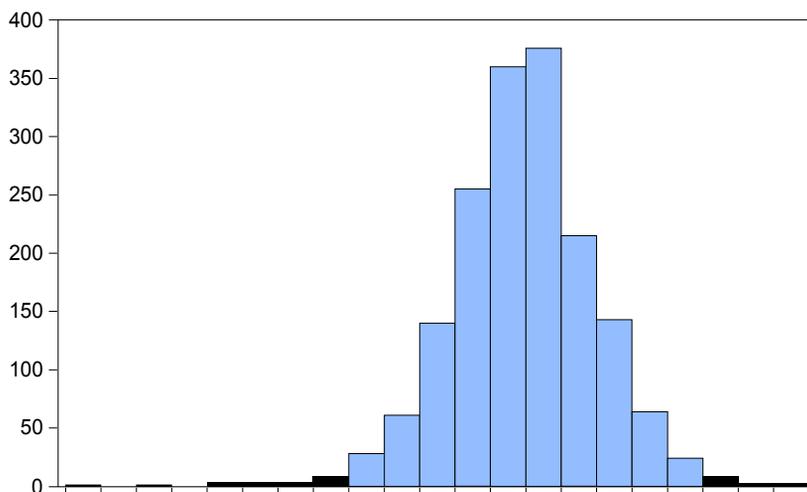
## APPENDIX Residual test

Date: 03/20/17 Time: 10:05  
Sample: 9/07/2010  
3/03/2017

Included observations: 1694

Auto correlation	Partial Correlation	AC	PAC	Q-Stat	Prob	
		1	0.014	0.014	0.3274	0.567
		2	-0.000	-0.001	0.3277	0.849
		3	-0.028	-0.028	1.6194	0.655
		4	0.020	0.021	2.2997	0.681
		5	-0.050	-0.051	6.5817	0.254
		6	0.004	0.005	6.6124	0.358
		7	-0.006	-0.005	6.6720	0.464
		8	-0.000	-0.003	6.6722	0.572
		9	0.039	0.042	9.3182	0.408
		10	0.048	0.044	13.252	0.210
		11	0.001	0.001	13.255	0.277
		12	0.007	0.008	13.328	0.346
		13	0.012	0.012	13.554	0.406
		14	-0.020	-0.018	14.211	0.434
		15	-0.058	-0.053	19.883	0.176
		16	0.007	0.009	19.970	0.222
		17	-0.011	-0.012	20.176	0.265

Auto correlation	Partial Correlation	AC	PAC	Q-Stat	Prob	
		18	0.021	0.019	20.942	0.282
		19	-0.034	-0.038	22.915	0.241
		20	-0.005	-0.012	22.950	0.291
		21	0.053	0.057	27.865	0.144
		22	0.046	0.039	31.470	0.087
		23	-0.018	-0.015	31.999	0.100
		24	-0.022	-0.016	32.858	0.107
		25	0.024	0.029	33.853	0.111
		26	-0.011	-0.009	34.055	0.134
		27	0.025	0.029	35.123	0.136
		28	-0.009	-0.007	35.256	0.163
		29	-0.003	-0.004	35.268	0.196
		30	-0.034	-0.036	37.232	0.170
		31	0.039	0.030	39.873	0.132
		32	-0.028	-0.029	41.251	0.127
		33	0.025	0.027	42.308	0.129
		34	-0.007	-0.012	42.403	0.153
		35	-0.001	-0.007	42.404	0.182
		36	-0.011	0.001	42.630	0.207



Series: Standardized Residuals  
Sample 9/07/2010 3/03/2017  
Observations 1694

Mean -0.026025  
Median -0.019700  
Maximum 3.669658  
Minimum -6.335468  
Std. Dev. 0.999052  
Skewness -0.267553  
Kurtosis 4.909524

Jarque-Bera 277.5775  
Probability 0.000000



Heteroskedasticity Test: ARCH

F-statistic	0.025406	Prob. F(1,1691)	0.8734
Obs*R-squared	0.025436	Prob. Chi-Square(1)	0.8733

Test Equation:

Dependent Variable: WGT\_RESID^2

Method: Least Squares

Date: 03/20/17 Time: 10:07

Sample (adjusted): 9/08/2010 3/03/2017

Included observations: 1693 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	1.001428	0.053938	18.56623	0.0000
WGT_RESID^2(-1)	-0.003876	0.024318	-0.159392	0.8734

R-squared	0.000015	Mean dependent var	0.997556
Adjusted R-squared	-0.000576	S.D. dependent var	1.981039
S.E. of regression	1.981610	Akaike info criterion	4.206877
Sum squared resid	6640.181	Schwarz criterion	4.213296
Log likelihood	-3559.121	Hannan-Quinn criter.	4.209254
F-statistic	0.025406	Durbin-Watson stat	1.999504
Prob(F-statistic)	0.873379		

## Bilingualism and its economic advantages

(Continued from p.268)

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