Economic Computation and Economic Cybernetics Studies and Research, Issue 1/2018; Vol. 52

Sebastian-Ilie DRAGOE, PhD Student Lucian Blaga University of Sibiu E-mail: dragoesebastian@yahoo.com Professor Camelia OPREAN-STAN Lucian Blaga University of Sibiu E-mail: camelia.oprean@ulbsibiu.ro

A NEW INTERNATIONAL MONETARY SYSTEM ON THE HORIZON?

Abstract: The international monetary system suffers from many imbalances that undermine the stability of the world financial system. The dollar is at the heart of this system. As a global currency, the dollar forms the bulk of international reserves held by central banks and is the most used currency in international commercial transactions. This demand creates a countervailing force that causes dollars to exit from US, thus producing a trade balance deficit. In this paper, we will support the widening of the SDR currency basket, demonstrating with the ARCH family models that the EUR / SDR exchange rate is less volatile than the EUR/USD exchange rate.

Keywords:*Triffin's dilemma, international monetary system, global currency, currency risk, GARCH.*

JEL Classification: B27, C58, G01, G15

I. Introduction

The Global Savings Glut (Bernanke, 2005) has prompted a surge in capital inflows into United States, leading to cheaper credit growth and increased access to finance. Excessive dependence on credit ratings, over indebtedness, the failures of supervisory and regulatory authorities and expanding funding associated with capital inflows contributed to the development of the US real estate bubble and the emergence of financial instability that led to the Great Recession (Bertaut et al, 2011). Increased credit availability and a large wealth effect have accentuated US productivity deficits against emerging economies and increased the US trade deficit. Also, the very high demand for dollars has reduced interest rates in the short and long term. The downward trend in interest rates contributed to the development of speculative bubbles on real estate and capital markets. Subsequently, short-term interest rates increased as a result of the monetary policy measures adopted by the Reserve System in order to achieve the objective of maintaining price stability, but also due to the increasing risks perceived by investors. They have changed their preferences and have invested in long-term securities, therefore decreasing long-term interest rates. This dynamic (inverted

yield curve) compressed the profit margin of financial institutions and caused financing difficulties for them because they are financed through short-term debt instruments and invest in long-term assets. Therefore, the role of the global dollar has contributed significantly to creating the imbalances underlying the outbreak of the 2008 global crisis.

In the context of very high private and public debt to GDP ratios, Keynesian remedies do not have a strong impact on economic growth, as public debt can't replace the adjustment of private balances too quickly or in the long run. On the other hand, austerity measures make it harder for the economy to return to the pre-crisis trend as it reduces aggregate demand. The logical solution implies improving trade imbalances by rethinking the role of the dollar in the international monetary system.

II. Literature Review

Deficiencies in international monetary systems have long been studied, whether we are talking about gold or fiat money. Gold can no longer cover the needs of the world economy, which leads to deflation. According to Bernanke (2012), during the Great Depression, deflation was stopped when the countries left the gold standard. But deflation is not the only problem faced by gold-based and fiat monetary systems. The most important dilemma is Triffin paradox, according to which other countries must also hold reserve currency, which makes dollars leave US borders, generating a current account deficit, with the consequence of weakening the US economy. If the United States would stop running balance-ofpayments deficits, the global economy would contract. If deficits continue, the most likely result would be rising inflation and loss of confidence in the dollar (Triffin, 1959).

Other imbalances include negative effects on global aggregate demand, when the accumulation of reserves is the result of current account surpluses and not just the result of a moderation in the impact of private foreign exchange inflows on the exchange rate, there is a global aggregate demand reduction (United Nations Report, 2009). Also, there is an exponential growth of dollar-denominated debt whenever it strongly appreciates against the local currency.

Over the years, several solutions have been proposed to solve the imbalances of the international monetary system, the most relevant being the adoption of a multipolar monetary system, the creation of a single global currency and the enlargement of the SDR (Xiaochuan, 2009) to become more attractive and widely used in international trade and in financial transactions.

Given the downward trend of the US economy's share of global GDP and the decline of the dollar in international reserves and transactions, a multipolar monetary system is configured, that can offer both advantages and disadvantages. The advantages lie in the diversification of the guaranteed assets (government securities) and in a greater capacity to ensure global liquidity, without the governmental debts of the states from which the key currencies come, to become unsustainable. The main disadvantage is the volatility of the exchange rate between

currencies used as reserve assets. In the case where central banks and private agencies respond to exchange rate fluctuations by changing the composition of their reserve assets, this would fuel the exchange rates instability.

A single global currency would amplify productivity gaps between states. Losing exchange rate policy, low-productivity economies will become even more unproductive because countries will not be able to reduce competitiveness losses by manipulating exchange rates, and stronger states will become even more productive, thereby developing strong crises. This phenomenon has been experienced by PIIGS (Portugal, Italy, Ireland, Greece and Spain) before the global financial crisis of 2008, when they have accumulated trade deficits. In addition, the monetary policy adopted by the Global Central Bank, which could be created to manage global liquidity, could have opposite effects on the each continent's economy (Krugman, 2009) (Dragoe, 2014).

In 2009, Central Bank Governor Zhou Xiaochuan proposed a supranational currency to compete with the US dollar. The banker advocated the creation of an "international reserve currency that is disconnected from individual nations and is able to remain stable in the long run, thus removing the inherent deficiencies caused by using credit-based national currencies" (Xiaochuan, 2009). Zhou Xiaochuan believes that this currency should be SDR, that it could be used in the future in international trade and that it has to incorporate more currencies of powerful economies to become more stable and more attractive. From October 1, 2016, with the renminbi being declared freely usable, the SDR currency basket contains the dollar, the euro, the pound sterling, the Japanese yen and the renminbi.

In the paper we propose to include the G20 countries' coins (the representative currency for the EU is the Euro) in the currency basket because of its economic and political power. This currency is not intended to replace all currencies but to circulate alongside other convertible currencies, to help hedge foreign exchange risk and to mitigate dollar imbalances.

III. Research methodology

In order to empirically prove the natural hedging property of the G20 SDR, we calculated its fictitious rate against the Euro using the weighted average of the exchange rates. Using the World Bank database, we have expressed the share of each country's GDP (for the Euro we have chosen the Eurozone, changing composition) in relation to G20 GDP (NY.GDP.MKTP.CD series - GDP at market prices expressed in current US\$ for the years 1998-2015). Quandl database was used for the exchange rates (this website presents the inverse quotation, we used the usual notation, the selected period being 30/09/1999 - 30/12/2016, daily data), containing 4502 daily quotes. In order to determine the artificial exchange rates of the extended SDR, the rates at year t were weighted according to the GDP size of the country from which the respective currency originated, at t-1. Of course, we can use the forecasts of the main international institutions (IMF, World Bank, BIS) for weighting, but for simplicity, the method outlined above was chosen. The ARCH family of models (ARCH, GARCH, IGARCH, EGARCH, TARCH and PARCH)

was used to estimate the daily return volatility of the EUR/Enlarged SDR and EUR/USD exchange rates.

The ARCH model was introduced by Engle (1982) and improved by Bollerslev (1986). Usually, when econometrists shape the relationship between two or more variables, they use the least squares method. But, when modeling errors and volatility, the ARCH / GARCH models are mostly used. The least squares method assumes that the error term's observations have a constant variance, meaning they are homoscedastic. Heteroscedasticity involves unequal variances of residual term and the autocorrelation of residuals.

In the presence of heteroscedasticity, regression coefficients estimated by the least squares method are unbiased, but standard errors and confidence intervals estimated by conventional procedures will be too tight, giving a false sense of precision. ARCH and GARCH are modelling heteroscedasticity and do not consider it a problem to be corrected (Engle, 2001). ARCH has the advantage of giving more importance to the recent weighted averages of square residuals and less to those in the distant past. This avoids the problems caused by the use of a standard deviation on short samples (too much white noise) or on too long samples (no longer relevant today) to quantify volatility (Engle, 2003).

ARCH model is composed of the following equations (Dutta, 2014):

$$Y_t = \varphi + \gamma_j * X_t + \varepsilon_t \tag{1}$$

$$\sigma^{2} = \omega + \sum_{i=1}^{q} \alpha_{i} * \varepsilon^{2}_{t-i}$$
⁽²⁾

where,

Y – dependent variable, φ – intercept, X – independent variable, ε_t - error term, γ – regression coefficient (slope), ω – intercept, α – "ARCH" parameter, σ^2 – current conditional variance

The variance equation of the GARCH model (Dutta, 2014):

$$\sigma^{2} = \omega + \sum_{i=1}^{q} \alpha_{i} * \varepsilon^{2}_{t-i} + \sum_{j=1}^{p} \beta_{j} * \sigma^{2}_{t-j}$$
(3)
$$\beta_{j} -,, \text{GARCH" coefficient}$$

The sum of the coefficients must be subunit and additionally, the coefficients of the ARCH and GARCH terms must be subunits and positive (≥ 0). The GARCH process (a, p) is stationary if:

The GARCH process (q, p) is stationary if:

$$\sum_{i=1}^{q} \alpha_i + \sum_{j=1}^{p} \beta_j < 0 \tag{4}$$

Unconditional variance can be defined as:

$$h_t = \frac{\omega}{1 - \alpha - \beta} \tag{5}$$

where

h_t – unconditional variance

If $\sum_{i=1}^{q} \alpha_i + \sum_{i=1}^{p} \beta_i = 1$ results in an IGARCH process

The disadvantage of the GARCH model is the assumption that conditional volatility is affected symmetrically by positive and negative innovations (Engle and Patton, 2001). The GARCH model assumes that only magnitude and not the sign of unanticipated excess returns determines the unconditional variance (long term, average and steady-state). EGARCH and TARCH models are frequently used to examine the impact of asymmetry on volatility.

EGARCH model was introduced by Nelson (1991). The conditional variance in EGARCH model is expressed as follows:

$$\operatorname{Ln}(\sigma^{2}) = \omega + \sum_{i=1}^{q} \alpha_{i} * \left| \frac{\varepsilon_{t-i}}{\sigma_{t-i}} \right| + \sum_{k=1}^{r} \delta_{k} * \frac{\varepsilon_{t-k}}{\sigma_{t-k}} + \sum_{j=1}^{p} \beta_{j} * \ln(\sigma^{2}_{t-j})$$
(6)
$$\delta_{k} - \text{leverage parameter}$$

If the coefficient δk is negative, bad news (ϵt -i <0) generate more volatility than good news (ϵt -i> 0), indicating the presence of leverage, while in the other situation, δk > 0, positive shocks (good news) produce more volatility than negative shocks (bad news). The leverage effect relates to increasing the debt/stock market capitalization ratio when the stock price decreases, which results in higher equity returns volatility, in other words, assets become riskier. Thus leverage is a negative correlation between volatility and return on assets (Black, 1976). In the case of exchange rates, there is usually no leverage effect (Engle, 2001).

TARCH model was proposed by Glosten et al (1993) and by Zakoian (1994). TARCH (q, k, p) is expressed in the following form (Schwert, 2010):

$$\sigma_{t}^{2} = \omega + \sum_{i=1}^{q} \alpha_{i} * \varepsilon_{t-i}^{2} + \sum_{k=1}^{r} \gamma_{k}^{*} \mathring{\Gamma}_{t-k}^{*} \varepsilon_{t-k}^{2} + \sum_{j=1}^{p} \beta_{j}^{*} * \sigma_{t-j}^{2}$$
(7)

$$\begin{array}{c}
1 & \text{dacă } \epsilon_t < 0 \\
\dot{\Gamma}_t = \begin{cases} \\ 0 & \text{dacă } \epsilon_t > 0 \\ \end{array}$$
(8)

All ARCH-GARCH models presented above use dispersion for volatility forecasting. Instead, the most commonly utilized tool for volatility modeling is the standard deviation. PARCH is a model that uses the standard deviation, not the variance for volatility modeling. Ding et al (1993) created the POWER ARCH model, also called PARCH. The expression of PARCH (q, p) is:

$$\sigma_{i}^{2} = \omega + \sum_{i=1}^{q} \alpha_{i}^{*} (|\varepsilon_{t-i}| - \gamma_{i}^{*} \varepsilon_{t-i})^{\delta} + \sum_{j=1}^{p} \beta_{j}^{*} \sigma_{t-j}^{\delta}, \qquad (9)$$

where $\delta > 0$. If all coefficients $\gamma i = 0$ there is no asymmetry. PARCH model (q, p) is reduced to GARCH model (q, p) if $\delta = 2$ and $\gamma i = 0$ (Mapa, 2003).

To choose the best model to estimate volatility, we have used the Akaike, Schwartz, and Hannan-Quinn information criterion minimization.

On the acquired variances following the application of the volatility models, the square root extraction operation was applied to determine the volatility (standard deviation) of studied exchange rate returns. The estimated volatility of the 2 time series by the six methods was compared according to the model used.

For the purpose of calculating the rate of return of the EUR / SDR artificial exchange rate and the rate of return of EUR / USD, the data series were processed as follows:

$$r_{t} = \ln\left(\frac{Quotation_{t}}{Quotation_{t-1}}\right)$$
(10)

 r_t – return at time t, In - natural logarithm, Quotation_t - exchange rate at time t

The time series were logged and tested for stationarity through ADF, PP, and KPSS tests. The Augmented Dickey-Fuller test is an improvement of Dickey-Fuller test. Dickey-Fuller describes an autoregressive process of Y series, in the form of:

$$\mathbf{Y}_{t} = |\boldsymbol{\Phi}|^{*} \mathbf{Y}_{t-1} + \varepsilon_{t}, \tag{11}$$

where: ε_t – error term

If the coefficient $|\Phi|<1$, the Y series is stationary, if $|\Phi|>1$, the series is nonstationary because in time the variance increases exponentially (Dickey and Fuller, 1979).

The innovation in ADF test consists of using an AR(p) model because AR(1) might not be suitable for estimating the Y_t series.

$$Y_{t} = \Phi_{1} * Y_{t-1} + \Phi_{2} * Y_{t-2} + \dots + \Phi_{p} * Y_{t-p} + \varepsilon_{t}$$

$$Y_{t} = (\Phi_{1} + \dots + \Phi_{p}) * Y_{t-1} + (\Phi_{2} + \dots + \Phi_{p}) * (Y_{t-1} - Y_{t-2}) + \dots + (\Phi_{p-1} + \Phi_{p}) * (Y_{t-p+1} - Y_{t-p}) + \varepsilon_{t}$$

$$(\Phi_{1} + \dots + \Phi_{p}) = \beta,$$

$$(\Phi_{2} + \dots + \Phi_{p}) * (Y_{t-1} - Y_{t-2}) + \dots + (\Phi_{p-1} + \Phi_{p}) * (Y_{t-p+1} - Y_{t-p}) = \sum_{j=1}^{p-1} \varphi_{j} * \Delta Y_{t-j} \qquad (12)$$

$$Y_{t} = \beta * Y_{t-1} + \sum_{j=1}^{p-1} \varphi_{j} * \Delta Y_{t-j} + \varepsilon_{t}$$

$$\Delta Y_{t} = (\beta - 1) * Y_{t-1} + \sum_{j=1}^{p-1} \varphi_{j} \Delta^{*} Y_{t-j} + \varepsilon_{t}$$

Null hypothesis $\delta = 0$ (Y_t is not a stationary time series) Alternative hypothesis $\delta < 0$ (Y_t is a stationary time series)

Another stationarity test is Phillips-Perron.Dickey-Fuller and Phillips-Perron are different in terms of statistical test. Phillips-Perron modifies the test so that additional lags are not required in the presence of error autocorrection (Mahadeva and Robinson, 2004). The KPSS test contains another approach. It starts from a regression between the dependent variable and a constant, followed by an autoregressive equation with a lag in which the dependent variable is intercept (see equations 1 and 2). It is tested whether σ_u^2 is 0.

$$X_t = c_t + \varepsilon_t$$
 (13)

$$c_t = c_{t-1} + u_t$$
 (14)

In order to model the analyzed time series with GARCH family, it is desirable that the time series don't have a normal distribution and exhibit fat tails, which implies volatility persistence. To test the normality of the distribution of the analyzed exchange rate returns, the Jarque-Bera test was performed. The formula for the Jarque-Bera test is $JB = n * [S^2 / 6 + (EK)^2/24]$, where S is the asymmetry coefficient of formula $\frac{\sum_{i=1}^{N} (xi - xaverage)^3}{(\sigma^2)^{3/2}}$, S = 0 if the distribution is normal, and EK is the excess of Kurtosis, EK = K-3, because in the case of a normal distribution Kurtosis equals 3.

$$K = \frac{1}{n} \frac{\sum_{i=1}^{N} (xi - xaverage)^4}{(\sigma^2)^2}$$
(15)

In order for the time series to contain ARCH terms, the returns need to be autocorrelated. In this respect, the correlogram of returns and squared returns is determined. The correlogram contains autocorrelation and partial autocorrelation functions. The autocorrelation function at lag k is calculated using the next formula (Codirlaşu et al, 2010):

$$p_{k=} \frac{\sum_{t=k+1}^{n} \frac{((y_t - y \text{ average})*((y_{t-k} - y \text{ average}))}{n-k}}{\sum_{t=1}^{n} \frac{(y_t - y \text{ average})^2}{n}}$$
(16)

The partial autocorrelation at lag k represents the regression coefficient of Y_{t-k} from an autoregressive equation composed of Y_t , the dependent variable, Y_{t-k} - the independent variable and the intercept.

IV. Quantitative analysis of the Enlarged SDR volatility

Being a currency basket which contains 17 currencies (ARS, AUD, BRL, CAD, CNY, EUR, GBP, IDR, INR, JPY, KRW, MXN, RUB, SAR, TRY, USD and ZAR) belonging to the most developed nations, the proposed currency can be considered as an appropriate means of payment to avoid currency risk.

		margea DDI	-)				
Data	EUR/SD	Renminbi	Euro	GBP	JPY	USD	Other
	R weight	Weight	Weight	weight	weight	weight	curencies
12/31/1999	0.7675	3.80%	25.51%	5.99%	14.87%	33.53%	16.30%
12/29/2000	0.7760	3.88%	24.40%	5.86%	16.17%	34.24%	15.46%
12/31/2001	0.7724	4.16%	21.52%	5.62%	16.78%	35.32%	16.60%
12/31/2002	0.7031	4.61%	22.38%	5.55%	14.82%	36.58%	16.05%
12/31/2003	0.6505	4.89%	23.48%	5.84%	13.67%	36.47%	15.65%
12/31/2004	0.6382	4.92%	25.80%	6.01%	13.16%	34.08%	16.03%
12/30/2005	0.6838	5.16%	26.37%	6.31%	12.71%	32.41%	17.04%
12/29/2006	0.6453	5.62%	25.46%	6.17%	11.69%	32.20%	18.86%
12/31/2007	0.6126	6.30%	25.15%	6.13%	10.38%	31.74%	20.30%
12/31/2008	0.5938	7.29%	25.99%	6.28%	9.26%	29.70%	21.47%
12/31/2009	0.5862	8.71%	26.34%	5.45%	9.54%	27.88%	22.09%

Table 1. EUR/SDR (Enlarged SDR)

12/31/2010	0.5968	10.12%	25.40%	4.69%	10.37%	28.57%	20.85%
12/30/2011	0.5736	11.12%	22.90%	4.43%	10.39%	27.28%	23.89%
12/31/2012	0.5532	12.47%	22.32%	4.30%	10.14%	25.56%	25.22%
12/31/2013	0.5203	13.87%	20.36%	4.29%	10.05%	26.17%	25.27%
12/31/2014	0.5602	15.20%	20.75%	4.30%	8.15%	26.40%	25.20%
12/31/2015	0.5886	16.15%	20.65%	4.62%	7.47%	26.80%	24.32%
12/30/2016	0.5954	17.86%	18.83%	4.64%	7.11%	29.27%	22.29%

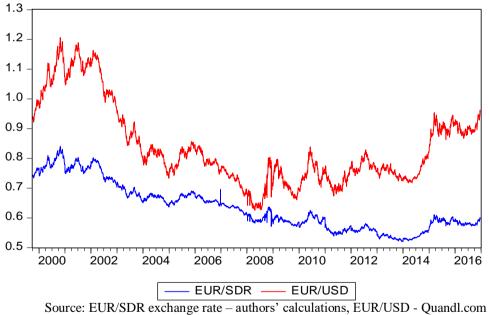
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Source: Author calculations using the World Bank databases and Quandl website

Table 1 shows the EUR/SDR fictitious rate at the end of each year from 1999 to 2016. It can be seen the downward trend of the Enlarged SDR expressed in Euro due to the decrease in the share of the freely usable currencies in the basket: the Euro, the British Pound and the US Dollar and the increase in the share of the renminbi and the other currencies.

The evolution of the EUR/Enlarged SDR and EUR/USD exchange rates is shown in Figure no. 1, from which it can be seen that the volatility of the EUR/Broad SDR is much lower compared to the volatility of the EUR/USD exchange rate.

Figure 1. Evolution of the EUR/Enlarged SDR exchange rates and EUR/USD, 1999-2016



With the purpose of proving the previous statement, we used Eviews 7.2 software for modeling volatility of exchange rate returns.

Null Hypothesis: L_EUF Exogenous: Constant Lag Length: 1 (Automati	-		1)		Null Hypothesis: L_EUF Exogenous: Constant Lag Length: 1 (Automat	-)	
			t-Statistic	Prob.*				t-Statistic	Prob.*
Augmented Dickey-Fulle Test critical values:	er test statistic 1% level 5% level 10% level		-54.75143 -3.431620 -2.861986 -2.567051	0.0001	Augmented Dickey-Full Test critical values:	er test statistic 1% level 5% level 10% level		-53.96270 -3.431620 -2.861986 -2.567051	0.0001
*MacKinnon (1996) one	-sided p-value	s.			*MacKinnon (1996) one	-sided p-value	S.		
Augmented Dickey-Full Dependent Variable: D(Method: Least Squares Date: 26/03/17 Time: 1 Sample (adjusted): 5/1 (Included observations:	L_EUR_SDR) 3:04 0/1999 30/12/2	016			Augmented Dickey-Full Dependent Variable: D(Method: Least Squares Date: 26/03/17 Time: 1 Sample (adjusted): 5/11 Included observations:	L_EUR_ÚSD) 3:17 0/1999 30/12/2	016		
Variable	Coefficient	Std. Error	t-Statistic	Prob.	Variable	Coefficient	Std. Error	t-Statistic	Prob.
L_EUR_SDR(-1) D(L_EUR_SDR(-1)) C	-1.250574 0.062224 -6.07E-05	0.022841 0.014890 6.61E-05	-54.75143 4.178896 -0.917646	0.0000 0.0000 0.3589	L_EUR_USD(-1) D(L_EUR_USD(-1)) C	-1.220384 0.057925 4.81E-06	0.022615 0.014893 0.000111	-53.96270 3.889313 0.043476	0.0000 0.0001 0.9653
R-squared Adjusted R-squared S.E. of regression Sum squared resid Log likelihood F-statistic Prob(F-statistic)	0.590221 0.590038 0.004434 0.088406 17994.98 3237.879 0.000000	Mean depend S.D. depende Akaike info co Schwarz crite Hannan-Quin Durbin-Wats	ent var riterion erion nn criter.	0.006926 -7.998213 -7.993938 -7.996706	R-squared Adjusted R-squared S.E. of regression Sum squared resid Log likelihood F-statistic Prob(F-statistic)	0.578189 0.578001 0.007415 0.247184 15682.06 3081.397 0.000000	Mean depeni S.D. depende Akaike info cr Schwarz crite Hannan-Quir Durbin-Wats	ent var riterion rion nn criter.	1.65E-06 0.011414 -6.970021 -6.965746 -6.968515 2.000347

Figure 2. ADF stationarity test

Source: Authors' calculations

Estimated δ for the L_EUR_SDR series is about -1.25, and for the L_EUR_USD series it is about -1.22. The null hypothesis is rejected if the t-statistic for $\delta = 0$ is lower than the critical value of the test for the chosen level of relevance.

Another test to determine the stationarity of data series is the Phillips-Perron test, represented in figure no. 3 below.

Figure 3. Phillips-Perron test

Exogenous: Constant	JR_SDR has a unit roo West automatic) using			Null Hypothesis: L_EU Exogenous: Constant Bandwidth: 7 (Newey-\	-		
		Adj. t-Stat	Prob.*			Adj. t-Stat	Prob.*
Phillips-Perron test st	atistic	-80.68631	0.0001	Phillips-Perron test sta	atistic	-78.75567	0.0001
Test critical values:	1% level	-3.431620		Test critical values:	1% level	-3.431620	
	5% level	-2.861986			5% level	-2.861986	
	10% level	-2.567050			10% level	-2.567050	

*MacKinnon (1996) one-sided p-values. Source: authors' calculations *MacKinnon (1996) one-sided p-values.

The value of the statistical test is lower than all levels of relevance. Thus, we can reject the null assumption that the analyzed time series are non-stationary.

To strengthen the belief that the time series are stationary, the KPSS test was also determined.

Figure 4. KPSS test

Null Hypothesis: L_EUR_SDR is Exogenous: Constant Bandwidth: 12 (Newey-West aut	<i>,</i>		Null Hypothesis: L_EUR_USD is Exogenous: Constant Bandwidth: 5 (Newey-West autor	·	
		LM-Stat.			LM-Stat.
Kwiatkowski-Phillips-Schmidt-S	hin test statistic	0.130472	Kwiatkowski-Phillips-Schmidt-Sł	nin test statistic	0.224860
Asymptotic critical values*:	1% level	0.739000	Asymptotic critical values*:	1% level	0.739000
	5% level	0.463000		5% level	0.463000
	10% level	0.347000		10% level	0.347000

Source: authors' calculations

The null hypothesis is "The series is stationary," and it is rejected if the statistical test value is higher than the critical value of the chosen level of relevance. The stationarity of the analyzed data series is also confirmed by this test.

Jarque-Bera test (see figure 5) is used to determine whether the time series follow a Gaussian function.

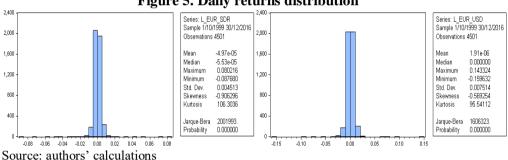


Figure 5. Daily returns distribution

L_EUR_SDR and L_EUR_USD series are not normally distributed as Kurtosis has values above 100 in the case of EUR/SDR and over 95 for EUR/USD returns, also the probability associated with the Jarque-Bera test is below the 0, 05 (null hypothesis: distribution is normal). The series display volatility clustering, meaning that large changes in the exchange rate returns are followed by large changes, and low changes are followed by low fluctuations.

To check if data series incorporate ARCH terms we have performed the correlogram of returns and squared returns.

Both correlograms indicated that returns and squared returns are autocorrelated, as the test probability is less than the 5% relevance level. Thus, the current returns depend on their past values.

Since this analysis refers to the volatility of the selected exchange rates returns and because the lack of the mean equation does not affect the volatility (Anatolyev and Tarasyuk, 2015), we will only focus on the variance equation. As the autocorrelation with one lag has the highest value, we will use the ARCH

family with a lag. For calculating volatility we used Generalised Error Distribution, given that data series are not distributed normally.

Figura 6. ARCH model

Dependent Variable: L_EUR_SDR Method: ML - ARCH (Marquard) - Generalized error distribution (GED) Date: 26/03/17 Time: 14:54 Sample: 1/10/1999 30/12/2016 Included observations: 4501 Convergence achieved after 38 iterations Presample variance: backcast (parameter = 0.7) GARCH = C(1) + C(2)*RESID(-1)*2				Dependent Variable: L_ Method: ML - ARCH (Ma Date: 26/03/17 Time: 1 Sample: 1/10/1999 30/1 Included observations: Convergence achieved Presample variance: ba GARCH = C(1) + C(2)*F	rquardt) - Gen 5:52 2/2016 4501 after 41 iteratio Ickcast (param	ins	stribution (G	ED)	
Variable	Coefficient	Std. Error	z-Statistic	Prob.	Variable	Coefficient	Std. Error	z-Statistic	Prob.
	Variance	Equation				Variance	Equation		
C RESID(-1)^2	1.06E-05 0.214677	3.88E-07 0.034717	27.42001 6.183571	0.0000 0.0000	C RESID(-1) ^A 2	3.38E-05 0.214144	1.23E-06 0.033434	27.50918 6.405060	0.0000 0.0000
GED PARAMETER	0.983712	0.010878	90.43366	0.0000	GED PARAMETER	1.074569	0.011283	95.23858	0.0000
R-squared Adjusted R-squared S.E. of regression Sum squared resid Log likelihood Durbin-Watson stat	-0.000121 0.000101 0.004513 0.091668 19345.04 2.353671	Mean depend S.D. depende Akaike info cri Schwarz criter Hannan-Quin	nt var terion rion	-4.97E-05 0.004513 -8.594551 -8.590278 -8.593045	R-squared Adjusted R-squared S.E. of regression Sum squared resid Log likelihood Durbin-Watson stat	-0.000000 0.000222 0.007513 0.254075 16630.73 2.306564	Mean depend S.D. depende Akaike info cri Schwarz critei Hannan-Quin	nt var terion rion	1.91E-06 0.007514 -7.388463 -7.384189 -7.386957

Source: authors' calculations

According to figure 6, the ARCH model is valid, the probability associated with the parameters is 0.0000 (<0.05), but the coefficient is relatively low, which means that the speed of volatility adjustment to market information is low.

Figure 7. GARCH model

Dependent Variable: L_EUR_SDR Method: ML - ARCH (Marquard) - Generalized error distribution (GED) Date: 26/03/17 Time: 15:20 Sample: 1/10/1999 30/12/2016 Included observations: 4501 Convergence achieved after 46 iterations Presample variance: backcast (parameter = 0.7) GARCH = C(1) + C(2)*RESID(-1)*2 + C(3)*GARCH(-1)					Dependent Variable: L_ Method: ML - ARCH (Ma Date: 26/03/17 Time: 1 Sample: 1/10/1999 30/1 Included observations: Convergence achieved Presample variance: ba GARCH = C(1) + C(2)*F	rquardt) - Gen 5:56 2/2016 4501 after 28 iteratic ickcast (param	ins eter = 0.7)		ED)
Variable	Coefficient	Std. Error	z-Statistic	Prob.	Variable	Coefficient	Std. Error	z-Statistic	Prob.
	Variance	Equation				Variance	Equation		
C RESID(-1)^2 GARCH(-1)	4.59E-07 0.048956 0.915441	4.47E-08 0.006187 0.006609	10.26222 7.912575 138.5149	0.0000 0.0000 0.0000	00 RESID(-1)*2 0.043249 0.004356 9.927889				0.0000 0.0000 0.0000
GED PARAMETER	1.012225	0.011989	84.42862	0.0000	GED PARAMETER	1.290376	0.021470	60.10141	0.0000
R-squared Adjusted R-squared S.E. of regression Sum squared resid Log likelihood Durbin-Watson stat	-0.000121 0.000101 0.004513 0.091668 19374.87 2.353671	Mean depend S.D. depende Akaike info cri Schwarz criter Hannan-Quin	nt var terion rion	-4.97E-05 0.004513 -8.607362 -8.601664 -8.605354	4513 Adjusted R-squared 0.000222 S.D. dependent var 0.0 7362 S.E. of regression 0.007513 Akaike info criterion -7.4 1664 Sum squared resid 0.254075 Schwarz criterion -7.4				1.91E-06 0.007514 -7.465360 -7.459662 -7.463352

Source: authors' calculations

As we can see in the chart above (figure 7), the C(1) coefficient is positive, ie when volatility increases also returns tend to increase. ARCH coefficient (C(2) or α) is statistically significant, but it is small in size, which means that conditional volatility does not change rapidly. C(3) coefficient represents the persistence of

conditional volatility. The value of β is superior to the ARCH coefficient, which indicates a stronger influence of past volatility on current volatility as compared to past shocks. The high value of the estimated β coefficient (C (3)) indicates that conditional volatility returns to the long-term average, but very slow because the shocks are protracted. Since a + $\beta < 1$, but $\alpha + \beta \approx 1$, periods of high volatility are followed by periods of high volatility, and periods of low volatility continue with low volatility.

The Integrated GARCH or IGARCH model (see Figure 8) is a GARCH model with the following parameter restriction: $\alpha + \beta = 1$

Figure 8. IGARCH model

Dependent Variable: L_EUR_SDR Method: ML - ARCH (Marquardt) - Generalized error distribution (GED) Date: 26/03/17 Time: 15:24 Sample: 1/10/1999 30/12/2016 Included observations: 4501 Convergence achieved after 21 iterations Presample variance: backcast (parameter = 0.7) GARCH = C(1)*RESID(-1)*2 + (1 - C(1))*GARCH(-1)					Dependent Variable: L_ Method: ML - ARCH (Ma Date: 26/03/17 Time: 1 Sample: 1/10/1999 30/1 Included observations: Convergence achieved Presample variance: ba GARCH = C(1)*RESID(rquardt) - Gen 6:05 2/2016 4501 after 22 iteratio ckcast (param	ns eter = 0.7)	istribution (G	ED)
Variable	Coefficient	Std. Error	z-Statistic	Prob.	Variable	Coefficient	Std. Error	z-Statistic	Prob.
	Variance	Equation				Variance	Equation		
RESID(-1)^2 GARCH(-1)	0.000193 0.999807	2.11E-05 2.11E-05	9.157540 47322.31	0.0000 0.0000	RESID(-1) ^A 2 GARCH(-1)	0.040883 0.959117	0.003194 0.003194	12.80190 300.3311	0.0000 0.0000
GED PARAMETER	0.918547	0.009292	98.85482	0.0000	GED PARAMETER	1.310874	0.018892	69.38761	0.0000
R-squared Adjusted R-squared S.E. of regression Sum squared resid Log likelihood Durbin-Watson stat	-0.000121 0.000101 0.004513 0.091668 19228.29 2.353671	Mean depend S.D. depende Akaike info cri Schwarz critei Hannan-Quin	nt var iterion rion	-4.97E-05 0.004513 -8.543119 -8.540269 -8.542115	R-squared Adjusted R-squared S.E. of regression Sum squared resid Log likelihood Durbin-Watson stat	-0.000000 0.000222 0.007513 0.254075 16790.19 2.306564	Mean depend S.D. depende Akaike info cri Schwarz criter Hannan-Quin	nt var iterion rion	1.91E-06 0.007514 -7.459760 -7.456911 -7.458756

Source: authors' calculations

Also in this case, the parameters are significant.

EGARCH model tests the asymmetry, ie if good news ($\varepsilon_{t-1}>0$) generates less volatility than bad news ($\varepsilon_{t-1} < 0$) or vice versa.

Figure 9. EGARCH model

Dependent Variable: L_EUR_SDR Method: ML - ARCH (Marquard) - Generalized error distribution (GED) Date: 26/03/17 Time: 15:34 Sample: 11/0/1999 30/12/2016 Included observations: 4501 Convergence achieved after 51 iterations Presample variance: backcast (parameter = 0.7) LOG(GARCH) = C(1) + C(2)*ABS(RESID(-1)/@SQRT(GARCH(-1))) + C(3) *RESID(-1)/@SQRT(GARCH(-1)) + C(4)*LOG(GARCH(-1))				Dependent Variable: L_ Method: ML - ARCH (Ma Date: 26/03/17 Time: 1 Sample: 1/10/1999 30/ Included observations: Convergence achieved Presample variance: ba LOG(0ARCH) = C(1) + 1 *RESID(-1)/@SQR?	rquardt) - Gen 6:06 2/2016 4501 after 33 iteratio ickcast (param C(2)*ABS(RES	ins ieter = 0.7) ID(-1)/@SQRTi	(GARCH(-1)))		
Variable	Coefficient	Std. Error	z-Statistic	Prob.	Variable	Coefficient	Std. Error	z-Statistic	Prob.
	Variance	Equation				Variance	Equation		
C(1) C(2) C(3) C(4)	-0.299734 0.118703 -0.000241 0.980956	0.031576 0.006961 0.005628 0.002650	-9.492531 17.05346 -0.042752 370.1869	0.0000 0.0000 0.9659 0.0000	C(1) C(2) C(3) C(4)	-0.133918 0.106821 0.006498 0.994670	0.015066 0.007811 0.005847 0.001342	-8.888503 13.67536 1.111309 741.1980	0.0000 0.0000 0.2664 0.0000
GED PARAMETER	1.012968	0.011625	87.13427	0.0000	GED PARAMETER	1.248737	0.021096	59.19320	0.0000
R-squared Adjusted R-squared S.E. of regression Sum squared resid Log likelihood Durbin-Watson stat	-0.000121 0.000101 0.004513 0.091668 19408.18 2.353671	Mean depend S.D. depende Akaike info cr Schwarz crite Hannan-Quir	ent var iterion rion	0.004513 -8.621718 -8.614595	R-squared Adjusted R-squared S.E. of regression Sum squared resid Log likelihood Durbin-Watson stat	-0.000000 0.000222 0.007513 0.254075 16804.23 2.306564	Mean depend S.D. depende Akaike info cr Schwarz crite Hannan-Quin	ent var iterion rion	1.91E-06 0.007514 -7.464667 -7.457544 -7.462157

Source: author's calculations

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The results of the applied EGARCH model (see Figure 9) indicate the presence of leverage effect on the EUR/Enlarged SDR but the coefficient (C(3)) is low in both cases (EUR/SDR and EUR/USD returns) and the probabilities associated with the leverage effect (coefficient C(3)) are > 0.05, therefore the previous interpretation does not apply, the sign of innovations does not influence volatility.

According to TARCH model (1,1,1), bad news at t-1 moment have an impact on volatility at time t equal to $(\alpha+\gamma)$ multiplied by the squared residuals of previous period, and good news has an impact equal to α multiplied by squared residuals at time "t-1". For innovations to have asymmetric impact on volatility, γ is required to be positive (Engle and Patton, 2001).

Figura 10. TARCH model

Dependent Variable: L_EUR_USD Method: ML - ARCH (Marquardt) - Generalized error distribution (GED) Date: 26/03/17 Time: 16:01 Dependent Variable: L_EUR_SDR Dependent Variaties L_EON_SOR Method: ML - ARCH (Marquardt) - Generalized error distribution (GED) Date: 26/03/17 Time: 15/28 Sample: 1/10/1999 30/12/2016 Included observations: 4501 Compregence colored the 252 Include Sample: 1/10/1999 30/12/2016 Included observations: 4501 Convergence achieved after 26 iterations Convergence achieved after 52 iterations Presample variance: backast (parameter = 0.7) GARCH = C(1) + C(2)*RESID(-1)*2 + C(3)*RESID(-1)*2*(RESID(-1)<0) + C(4)*GARCH(-1) Presample variance: backast (parameter = 0.7) GARCH = C(1) + C(2)*RESID(-1)^2 + C(3)*RESID(-1)^2*(RESID(-1)<0) + C(4)*GARCH(-1) Variable Coefficient Variable Coefficient Std. Error z-Statistic Std. Error z-Statistic Prob Prob Variance Equation Variance Equation C RESID(-1)^A2 2.51E-07 5.53E-08 4.537095 7.424638 4.37E-07 4.27E-08 10.22691 0.0000 0.0000 C RESID(-1)^A2 0.048989 0.006598 0.058870 0.010106 5.825155 0.0000 0.0000 RESID(-1)^2*(RESID(-1)<0) GARCH(-1) 0.019042 0.011205 -1 699399 0.0892 RESID(-1)*2*(RESID(-1)≤0) -0.012531 0.007640 -1.640173 0.1010 0.917253 GARCH(-1) 0.951953 0.003963 240.1802 0.0000 0.006393 143.4857 0.0000 GED PARAMETER 0.0000 GED PARAMETER 1.013246 0.011957 84.74088 0.0000 1.291472 0.021700 59.51595 R-squared Adjusted R-squared -0.000000 1.91E-06 -0.000121 -4.97E-05 Mean dependent va R-squared Mean dependent var Adjusted R-squared 0.004513 0.000222 S.D. dependent var 0.007514 0.000101 S.D. dependent var Akaike info criterion S.E. of regression Sum squared resid 0.004513 -8.607463 S.E. of regression 0.007513 Akaike info criterion -7 465442 Sum squared resid Log likelihood 0.254075 16805.98 2.306564 0.091668 Schwarz criterion -8.600340 Schwarz criterion -7 458310 -7.462932 Hannan-Quinn criter Hannan-Quinn criter Log likelihood 19376.10 -8.604954 Durbin-Watson stat Durbin-Watson stat 2.353671

Sursa: author's calculations

In Figure 10 we can see that γ (C(3)) is negative in both cases and that the probabilities associated with this coefficient are higher than 0.05, which means there is no leverage effect.

Method: ML - ARCH (Ma Date: 26/03/17 Time: 1 Sample: 1/10/1999 30/1 Included observations: Convergence achieved Presample variance: ba @SQRT(GARCH)*C(5)	Dependent Variable: L_EUR_SDR Method: ML - ARCH (Marquard) - Generalized error distribution (GED) Date: 26/03/17 Time: 15:36 Sample: 1/10/1999 30/12/2016 Included observations: 4501 Convergence achieved after 65 iterations Presample variance: backcast (parameter = 0.7) @SQRT(GARCH)*C(5) = C(1) + C(2)*(ABS(RESID(1)) - C(3)*RESID(-1))*C(5) + C(4)*@SQRT(GARCH(-1))*C(5)					6:11 2/2016 4501 after 40 iteratio ckcast (param	eter = 0.7) ABS(RESID(-1		ŗ
Variable	Coefficient	Std. Error	z-Statistic	Prob.	Variable	Coefficient	Std. Error	z-Statistic	Prob.
	Variance	Equation				Variance	Equation		
C(1) C(2) C(3) C(4) C(5)	3.29E-05 0.059199 -0.073905 0.944771 1.067931	1.52E-05 0.007058 0.057512 0.005185 0.081158	2.166926 8.387344 -1.285039 182.2281 13.15858	0.0302 0.0000 0.1988 0.0000 0.0000	000 C(2) 0.048097 0.005907 8.14227 988 C(3) -0.064711 0.049740 -1.30096 000 C(4) 0.954721 0.003884 245.796				0.0752 0.0000 0.1933 0.0000 0.0000
GED PARAMETER	1.008269	0.011836	85.18735	0.0000	GED PARAMETER	1.276782	0.022264	57.34829	0.0000
R-squared Adjusted R-squared S.E. of regression Sum squared resid Log likelihood Durbin-Watson stat	-0.000121 0.000101 0.004513 0.091668 19405.54 2.353671	Mean depend S.D. depende Akaike info cr Schwarz crite Hannan-Quin	ent var iterion rion	0.004513 -8.620103 -8.611556	R-squared Adjusted R-squared S.E. of regression Sum squared resid Log likelihood Durbin-Watson stat	-0.000000 0.000222 0.007513 0.254075 16809.87 2.306564	Mean depend S.D. depende Akaike info cr Schwarz crite Hannan-Quir	ent var iterion rion	1.91E-06 0.007514 -7.466728 -7.458180 -7.463716

Figura 11. PARCH model

Sursa: author's calculations

According to the results of PARCH (1.1) (see Figure 11), there is no leverage effect of volatility for the studied returns because the probability associated with the coefficient γ (C(3)) is above the 5% chosen level of relevance, meaning that the parameter is not statistically significant. The intercept in the case of EUR/USD returns is not significant at the level of relevance chosen. Otherwise, the coefficients are significant, indicating a strong influence of past volatility on current volatility.

All applied ARCH models have removed the autocorrelation of residuals (standardized residuals correlogram, square residuals correlation and ARCH-LM test). Selecting the best model is done by using the information criteria for the models where all the coefficients are significant. Therefore, the EGARCH, TARCH and PARCH models are not included in this comparison (the asymmetry coefficient is not significant and for applied PARCH model to L_EUR_USD series, the intercept is also not significant). The appropriate model for volatility estimation contains the minimum values of the information criteria. For both the EUR/Enlarged SDR and EUR/USD, the best model is GARCH (see Table 2).

EUR/Enlarged SDR			
Information Criterion	ARCH	GARCH	IGARCH
Akaike	-8.59455	-8.60736	-8.54312
Schwarz	-8.59028	-8.60166	-8.54027
Hannan-Quinn	-8.59305	-8.60535	-8.54212
EUR/USD			
Information Criterion	ARCH	GARCH	IGARCH

Table 2. Comparison of volatility models

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Akaike	-7.38846	-7.46536	-7.45976
Schwarz	-7.38419	-7.45966	-7.45691
Hannan-Quinn	-7.38696	-7.46335	-7.45876

Source: authors' calculations

Volatility (standard deviation) was calculated by extracting the square root of the estimated variances using the ARCH family and plotted in Figure 12. For all models the volatility of EUR/Enlarged SDR is low compared to the EUR/USD, except for a few moments in 2007 when there were turbulences in the major financial centers.

.07 04 .06 .05 03 .04 .03 02 .02 01 01 .00 -00 -2000 2002 2004 2006 2008 2010 2012 2014 2000 2002 2004 2006 2008 2010 2012 2014 201.6 ARCH_STD_DEV_L_EUR_SDR ARCH_STD_DEV_L_EUR_USD GARCH_STD_DEV_L_EUR_SDR GARCH_STD_DEV_L_EUR_USD .05 .05 .04 .04 .03 .03 .02 .02 01 0' .00 .00 2000 2002 2006 2008 2010 2012 2014 2016 2002 2008 2010 2014 2004 2000 2004 2006 2012 2016 IGARCH_STD_DEV_L_EUR_SDR IGARCH_STD_DEV_L_EUR_USD TARCH_STD_DEV_L_EUR_SDR TARCH_STD_DEV_L_EUR_USD .032 .040 .028 .035 .024 .030 .020 .025 016 .020 .012 .015 .010 .008 004 .005 .000 .000 2002 2000 2002 2004 2006 2008 201 0 2014 2000 2004 2006 2008 2010 2012 2014 2016 2012 2016 EGARCH_STD_DEV_L_EUR_SDR EGARCH_STD_DEV_L_EUR_USD PARCH_STD_DEV_L_EUR_SDR PARCH_STD_DEV_L_EUR_USD Sursa: authors' calculations

Figure 12. Estimated volatility (standard deviation) of exchange rate returns

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V. Conclusions

Triffin's dilemma highlights the economic weakness of the United States caused by the global role of the dollar, namely: chronic deficits of the trade balance.

In the age of globalization, it is imperative to develop a global currency with a flexible but relatively stable exchange rate that reflects the state of the global economy in order not to affect global trade.

In this context, the Enlarged SDR, consisting of the G20 member states' currencies, is the most effective solution among the proposed ones. This currency would reflect the economic evolution of the most powerful states at economic, commercial and political level. Being a currency basket, exchange rate volatility is naturally lower than the dollar. To prove this hypothesis with empirical approach, we used the ARCH-GARCH models and the GARCH extensions to compare the volatility of exchange rate returns. The results confirm this hypothesis, with all the models showing a reduced volatility of the Broad SDR when compared to the dollar.

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