Cyclical Behavior of Systemic Distress in the Banking Sector: An Empirical Investigation[1]

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Abstract

In this paper we aim at identifying cyclical behavior of banks' systemic risk contribution and exposure. Using a sample of 789 banks from OECD and EU-28 countries, we document that both systemic risk contribution and exposure is positively related to business cycle. That is, systemic risk starts to accumulate in the financial sector during periods of boom, i.e., when the output gap is positive. Furthermore, during periods of robust economic growth, the level of credit tends to increase dramatically, going hand in hand with asset and property prices developments. These variables are associated with financial cycles and their behavior amplifies the economic cycle which can result, under certain conditions, in a financial crisis. We find that contribution to system-wide distress moves procyclically during credit cycles, house and equity cycles, but the results for credit cycles lack statistical significance. As Peydró (2013) points-out, if credit expansion has economic fundamentals and is demand-driven, it could be harmless for systemic risk. In terms of banks' exposure to systemic distress, it evolves procyclically during credit and house cycles, and counterciclycally during equity cycles. Our index of financial cycle constructed using both macroeconomic and financial variables confirms the pattern of systemic risk to evolve procyclically. Additionally, the empirical analysis shows that both bank-specific and macroeconomic factors influence banks' systemic stress. Particularly, size, loan loss provisions and inflation positively affect systemic risk contribution and exposure of the banks, whereas capitalization, the share of loans in total assets, the share of non-interest income in total revenue, financial openness and financial freedom help banks in reducing their systemic importance. The results remain robust after controlling for nesting and possible reverse causality issues, and after employing different techniques for separating cycles from the trend.

Key-words: Systemic risk; Business cycle; Financial cycle; Financial regulation; Bank fragility

JEL classification: G21; G28; E30

[1] This paper contains 24 pages, excluding first page and bibliography, but including the Appendix.

A common response to those who propose that policymakers react to the development of system-wide vulnerabilities is that these vulnerabilities cannot be identified ex-ante, or at least cannot be identified any better by policymakers than by the market as a whole. As a result, the best that policymakers can do is to establish a regulatory framework that contributes to financial stability, and be prepared to act quickly whenever financial instability threatens the health of the macroeconomy.
(Borio et al., 2001, p.42)

1. Introduction and related literature

In the aftermath of the global financial crisis (GFC) of 2007-2009 which impacted severely the real economy (see e.g. Jorda et al., 2013 and Mclean and Zhao, 2014), there was a renewed interest from both academics and regulators in financial institutions' systemic behavior. Before this episode, the microprudential paradigm (Basel I and Basel II approaches) was used to describe financial stability: it assumes that financial instability is exogenous to the financial system, and risks should be assessed on an individual basis (i.e., stand-alone risks) using, for instance, Value-at-Risk (VaR) methodology.[2] Hence, it ignores the spillover effects between institutions. However, the current crisis demonstrated that this paradigm is obsolete – it completely ignored the negative externalities posed by individual financial institutions, creating systemic risk[3] for the overall economy as was the case with Lehman Brothers –, and a new one has emerged, i.e., the macroprudential paradigm (Basel III approach). Macroprudential policies focus on the system as a whole and try to limit the impact of the financial crises on real economy. Within this framework, the risk comes from inside of the financial system and propagates rapidly because institutions are interconnected, thus taking into account the spillover effects between them. Therefore, the ultimate objective of the macroprudential supervision is to prevent systemic risk proliferation, and if prevention fails, to lull the impact when it materialises (Frait and Komárková, 2011). One way in achieving this objective is

[2] For a detailed theoretical description of the VaR models, see Jorion (1997), Dowd (1998), Saunders (1999), Danielsson (2011), and Hull (2012).
[3] Freixas et al. (2014) define systemic risk as "the risk of threats to financial stability that impair the functioning of the financial system as a whole with significant adverse effects on the broader economy". For other definitions and surveys, see De Bandt and Hartmann (2000) and Silva et al. (2017).

through the implementation of adequate capital and liquidity buffers that would act as built-in stabilisers when a downturn occurs, absorbing the adverse financial consequences due to unexpected capital shocks. Under the Basel III (BCBSa, 2010), banks are required to create a "discretionary countercyclical buffer" within a range of 0–2.5% of common equity that is designed to reduce loan growth during credit booms (financial expansion, credit-to-GDP ratio exceeds its long-run trend by 2%) and utilize it in a stress situation (financial contraction) (Drehmann et al., 2010).

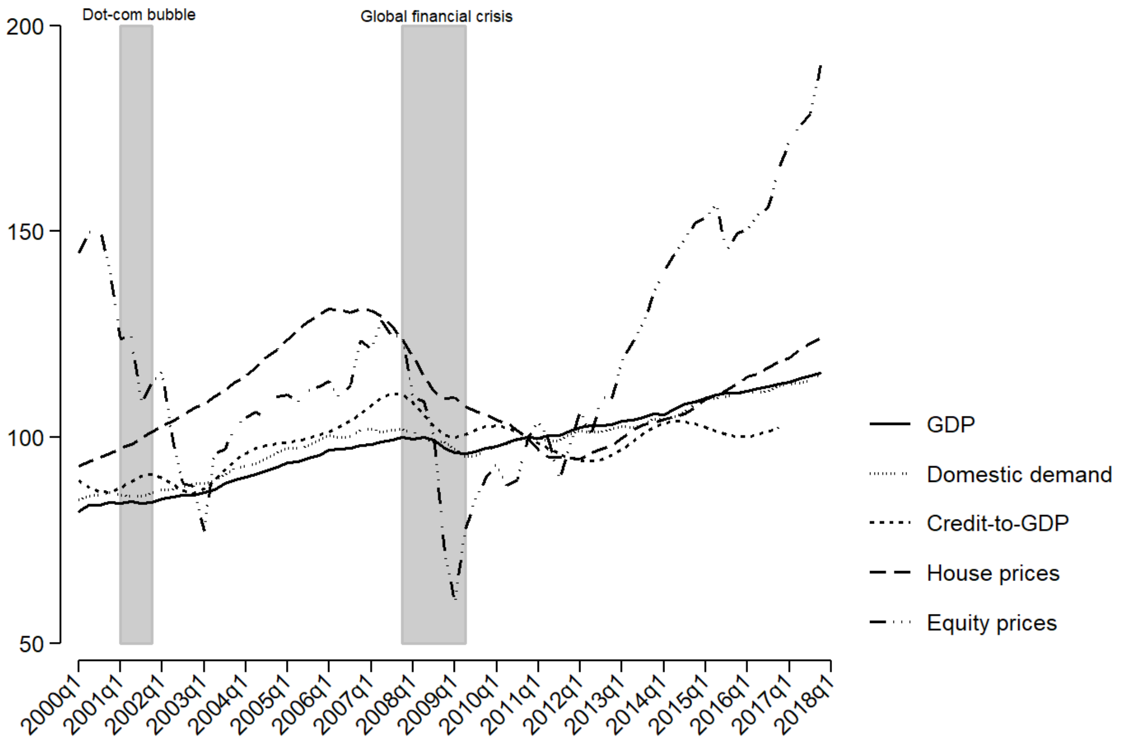

Figure 1. GDP, domestic demand, credit-to-GDP ratio, house prices and equity prices in real terms and seasonally adjusted in the US from 2000q1 to 2017q4. Each variable is expressed as an index, 2010q4=100. Shaded areas correspond to crisis periods in the NBER chronology.

In the run-up of the GFC, credit and asset prices rose in an unprecedented way, deviating from their fundamental trend, and caused distortions in the allocation of resources. Typically, in such a period, firms' profits tend to increase and customer expectations are overly optimistic. Bank lending and the level of the debt in the economy increase due to an expansion in the aggregate demand. In such exuberance when the value of collateral is high, banks may underestimate their risk exposure and relax their criteria in selecting customers, which in turn can lead to deterioration in the quality of the borrowers. When the process is reversed due to an exogenous shock, borrowers' profitability worsens, asset prices decreases and the value of collateral diminishes. As a consequence, there is an accumulation of non-performing loans and a decline in capital ratios which gives rise to high level of banks' losses (cyclicality). As the quality of the credit deteriorates, the level of the credit supply in the economy is notable reduced, which amplifies the slump (procyclicality) (Quagliariello, 2008). Acharya and Naqvi (2012) note that in the US during 2002-2007 period house prices grew at a rate of 11% per year with no evidence of an increase in creditworthiness of the borrowers. Moreover, Jorda et al. (2013) point out that there was an increase in credit too: in 2008, the ratio of financial assets to GDP was 3.5:1, as compared to only 1.5:1 in 1975. In Figure 1 is depicted the evolution of several macro and financial variables in the US from 2000q1 to 2017q4. The house prices and domestic credit to GDP ratio followed an upward pace even during the dot-com bubble, when GDP, domestic demand and equity prices fell. However, all decreased in the eve of GFC, with house and equity prices starting to decline even a few quarters before the official recession dates registered by the National Bureau of Economic Research (NBER).

Borio et al. (2001) argue that typically the problems that accumulate in the financial system are due to the fact that institutions underestimate their exposure to a common factor, which in his view is business / financial cycle. In the same line, Peydró (2013) points out that ex-ante financial disruptions are a key determinant of systemic risk and understanding of cyclical movements of financial indicators is sine qua non for a correct design of macroprudential policies (Stremmel, 2015). Business cycle[4] is shortly defined as the nonseasonal fluctuations in the aggregate economic activity (Burns and Mitchell, 1946; Zarmowitz, 1992), where the output, i.e., the real GDP, is typically used as the main indicator to characterize the business cycle. As concerning the financial cycle, there is no consensus on its definition (Borio, 2014). It is usually described in terms of fluctuations of credit and property prices (Drehmann et al., 2012; Borio et al., 2018), and it's widely accepted that the length of financial cycle (usually eight to twenty years) is longer than the length of business cycle (usually two to eight years), and it has wider amplitude. Furthermore, empirical

[4] Throughout this paper, business and economic cycle terms will be used interchangeably.

investigation of Claessens et al. (2012) suggests a strong interaction between different phases of business and financial cycles. They bring into focus interesting results: recessions that are accompanied with financial imbalances are longer and deeper than other recessions, and if in the recovery phase there are house or credit booms, the output growth is enhanced. Schularick and Taylor (2012) present similar insights from their analysis of 14 advanced economies over the years 1870–2008: the built-up of credit during an upturn and the severity of recessions that ensue are closely related, regardless the type of recession.[5]

In an extensive documentation of the studies on the impact of macroeconomic factors on bank stability, Quagliariello (2008) reinforces the procyclicality of bank behavior (see also Williamson, 1987; Kiyotaki and Moore, 1997; Bernanke et al., 1999). The phenomenon of bank procyclicality has two meanings. The first one refers to the macroeconomic concept, i.e., the tendency of financial variables to fluctuate around a trend during the economic cycle or, in other words, the comovement of banking variables with the output. The second one deals with the mechanism by which banking shocks are propagated to the real economy (i.e., the feedback effect). In the present study, we will mostly refer to the first definition outlined. The bank procyclicality has been studied for multiple bank aspects, such as bank stability, capital buffer, non-performing loans, loan loss provisions, or bank profitability. In a recent study of Bouheni and Hasnaoui (2017) investigating the impact of business cycle on bank stability on 722 commercial bank from the Eurozone over 1999-2013 period, their findings showcase a negative relationship between business cycle (proxy GDP) and the likelihood the bank insolvency (proxy z-score[6]), i.e., a procyclical behavior of the banks, supporting previous findings that bank default is increasing during recessions (Allen and Saunders, 2003; Curry et al., 2008). Shim (2013) brought forth a similar study using quarterly data, reaching the same conclusion, for the US bank holding companies. Carvallo et al. (2015) examine how capital buffers fluctuates over the business cycle in 13 Latin American and

[5] Other similar studies (e.g., Reinhart and Rogoff, 2008; 2009a; 2009b; 2011; Kaminsky and Reinhart, 1999; Jordà et al., 2013) point out the leverage (credit) is a first-order factor in explaining banking crises and the fact that the effect on the real economy is worse when the crisis is preceded by a credit boom. Therefore, there seems to be a consensus that "leverage is the Achilles heel of capitalism" as James Tobin put it in his book review on *Stabilizing an unstable economy* by Hyman P. Minsky (Tobin, 1989).

[6] Higher values for the z-score indicate lower probability of default for a bank.

Caribbean countries for the period 2001–2012, suggesting an inverse relationship between regulatory capital buffers and GDP growth for five countries, and direct for six. Shim (2013) finds a negative association between business cycle and capital buffer for the US. Salas and Saurina (2002) undertake an analysis on determinants of credit risk of Spanish commercial and savings banks in the period 1985–1997 and report that business cycle has a negative and significant impact on problem loans. Laeven and Majoni (2003) and Cavallo and Majnoni (2002) find a negative relationship between loan loss provisions for large commercial banks from various countries and real GDP growth, suggesting that banks make provisions during and not before crises, thus amplifying the effects of the negative phase of the business cycle. Similar results are provided by Quagliariello (2007), Bikker and Metzemakers (2005), Bikker and Hu (2002), and Arpa et al. (2001). Concerning bank profitability, Albertazzi and Gambacorta (2009) find a positive and significant association between business cycle and bank profitability and this can be attributed to improved economic conditions that lead to a rise in lending demand by households and firms. Bikker and Hu (2002) document similar findings.

In this study, we aim at enhancing current knowledge with respect to procyclical behavior of the banks. More specifically, our approach is orientated towards banks' systemic risk contribution and exposure, and how it fluctuates over the business and financial cycle. Using a sample of 789 banks from 36 countries from OECD and the EU-28 for a period that spans from 2000q1 to 2017q4, we document a positive and significant link between systemic risk contribution (proxy ΔCoVaR) and systemic risk exposure (proxy MES) of banks and business cycle (proxy real GDP cycle from one-sided Hodrick–Prescott filter[7][8]). That is, the system-wide distress of the banks is procyclical in relation with output gap. In our baseline analysis, we assume a delay in the transmission of the information from the real economy to banks of one quarter, but the results stay robust even for four quarters. This translates into the fact that systemic risk in the banking sector starts to accumulate well before the upswing in GDP. For bank regulators this is of paramount

[7] For methodological aspects of the two systemic risk measures and cycle extraction, see the next section.

[8] Although the one-sided Hodrick–Prescott filter (Hodrick and Prescott, 1997) is our main method used for cycle extraction and has several advantages that we discuss in the next section, we use other alternatives to test the robustness of the findings.

importance since after the GFC systemic risk and contagion spillovers in banking sector are considered primary tasks, as the direct costs of bank defaults are much greater than the costs of defaults of non-financial companies (James, 1991). Also, this can help authorities to decide when exactly they should impose the increase in "mandatory capital conservation buffer" of 2.5% of risk-weighted assets, and, in case of a higher credit gap (credit boom) the discretionary counter-cyclical buffer" of up to 2.5% established within the Basel III framework.

We identify a direct relationship with financial cycle too, using three different proxies: credit-to-GDP ratio gap, house prices gap, and equity prices gap. As in the case of output, we extract the cycle employing one-sided Hodrick–Prescott filter, but with a higher smoothing parameter. The most notable difference, however, is for credit cycle: contribution to systemic risk is positively related to credit cycle but statistically insignificant, whereas a positive deviation from the trend increases banks' exposure to system-wide distress. This is in line with IMF's (2002) analysis of 170 countries, concluding that two thirds of credit booms did not end up in a financial crisis, and that important part of credit booms may be driven by strong economic fundamentals and thus do not pose a risk for systemic risk (Peydró, 2013). Additionally, our empirical analysis shows that both bank-specific and macroeconomic factors influence banks' systemic stress. Particularly, size, loan loss provisions and inflation positively affect systemic risk contribution and exposure of the banks, whereas capitalization, the share of loans in total assets, the share of non-interest income in total revenue, financial openness and financial freedom help banks in reducing their systemic importance. However, the sign of the control variables tends to vary across business and financial cycle proxies, and across systemic risk contribution and exposure.

Further, we develop a synthetic index of financial cycle using both macro and financial variables. Specifically, we employ output gap, domestic demand gap (with a statistical filter over a higher frequency), credit-to-GDP gap, and house prices gap. Domestic demand may be more driven by financial factors, such as the level of the credit in the economy and the house prices, than the GDP. Therefore, as in Comunale (2015) we use domestic demand gaps filtered with the same smoothing parameter as in the case of credit and house cycles. The results confirm the procyclicality of systemic risk in the banking sector.

We contribute to the extant literature in several stances. First of all, most of the authors simply approximate the business cycle with the real GDP (see e.g., Shim, 2013; Bertay et al., 2015; Creel et al., 2015; Carvallo et al., 2015; DeYoung and Jang, 2016; Bouheni and Hasnaoui, 2017). Isolating the cycle from the trend, we are thus able to assess only the unobserved cyclical component of the variable we are interested in, i.e., the business cycle per se or the short-run fluctuations, without the alteration of the long-run effects that might change too slow. Other method in identifying phases of expansion (previous peak to actual trough) and contraction (peak to trough) and hence cycles (trough from previous trough and peak from previous peak) is based on Harding and Pagan's (2002) methodology used by NBER for dating business cycles in the US (turning points). However, this algorithm requires a long timespan in order to detect at least two peaks (for expansion cycle) or two troughs (for contraction cycle). For example, in our initial sample of 41 countries (OECD plus EU-28) we were able to find cycles only for 16 countries for 2000q1-2017q4 period. Therefore, the detrending method adopted to extract business cycles is the most suitable for our purpose since we do not lose any observation. Second, we provide additional findings for systemic risk determinants using higher frequency of data, i.e., quarterly data. The most of the work in this field uses yearly data (see, among others, Beltratti and Stulz, 2012; Weiß est al., 2014; Laeven et al., 2016; Zedda and Cannas, 2017). Also, we do not emphasize only on large banks (e.g., Laeven et al., 2016), but we extend the analysis to all banks from specific advanced and developing economies (OECD plus EU-28) for which we have available data in computing systemic risk metrics as suggested by Brunnermeier et al. (2009), arguing that smaller institutions can turn out to be systemic as part of a herd. Third, to the best of our knowledge, there are no other similar investigations to particularly assess how systemic riskiness in the banking sector is related to business and financial cycle.

The remainder of our paper is structured as follows: In Section 2 we describe the systemic risk measures, cycle extraction techniques and the methodology we employ, in Section 3 we present the empirical findings, in Section 4 we run additional robustness tests, and in Section 5 we conclude.

2. Empirical framework and methodology

2.1. Systemic risk measures

Systemic risk measures are estimated for each bank individually and are intended to identify systemically important banks based on their contribution or exposure to systemic risk. There are two common approaches used to determine contribution or exposure to systemic risk. The first one deals with positions and risk exposures, and this is confidential information given by the banks the regulatory authorities. The second one relies on market data, such as stock returns and CDS spreads and has especially been developed in the last decade by the researchers as an alternative to the first one which uses accounting data. Bisias et al. (2012) provide an extensive survey of 31 measures of systemic risk.

In this study we will employ two systemic risk (SR) measures. The first one is Conditional Value at Risk (CoVaR) of Adrian and Brunnermeier (2016). It is based on the well-known Value at Risk (VaR) measure which expresses the maximum possible loss that an asset, a portfolio or an institution (a bank, in our case) could register for a given confidence level *α*, usually set at 95% or 99% level, over a specific period of time. More precisely, VaR involves estimations of each bank's q^{th} quantile[9] of the following loss function:

$$q = \Pr\,(R^i_{Market\ Assets,t}\ \leq\ VaR^i_{q,t} \tag{1}$$

where $R^i_{Market\ Assets,t}$ is the bank's *i* market value of assets at time *t* determined by adjusting the book value of total assets by the ratio between market capitalization (market value of equity) and the book value of equity. VaR is the tail risk measure of individual risk of a bank (idiosyncratic risk) used in the context of microprudential supervision. Thus, it fails to capture the risk of the whole system. In order to assess the contagion spillovers from a bank to the whole system in the case of a severe reduction of the market assets, one can apply the CoVaR methodology. It implies the estimation of the system's q^{th} quantile of the returns distribution over a given period

[9] Following Adrian and Brunnermeier (2016), all our systemic risk indicators are estimated for a 5% quantile.

of time ($R^{System}_{Market\ Assets,t}$), conditioned on the event that each bank registers its maximum possible loss of the returns for the same significance level. More precisely, we focus on the loss generated by the reduction of the banks' market value of total assets under extreme events, as in Adrian and Brunnermeier (2016):

$$q = \Pr\left(R^{System}_{Market\ Assets,q} \leq CoVaR^{System|R^{i}_{Market\ Assets,t}=VaR^{i}_{q,t}}_{q,t} | R^{i}_{Market\ Aseets,t} = VaR^{i}_{q,t}\right.$$

(2)

where system is defined by the market value of total assets of the sample. Thus, CoVaR is the VaR of the banking system conditional on banks being under distress, being a good indicator of tail-event linkages between financial institutions (Diebold and Yılmaz, 2014). Also, banks are treated as part of the system, and systemic risk would indicate the spread of contagion through the system (Andrieș et al., 2018).

In order to compute VaR and CoVaR we use Quintile Regression (QR) developed by Koenker and Bassett (1978). This method allows us to estimate the dependent variable's quantiles conditioned on the explanatory variables, being more robust in the presence of extreme market conditions (Nistor and Ongena, 2019). Moreover, we use the method of Machado and Santos Silva (2013) which permits the standard errors to be asymptotically valid in the presence of heteroskedasticity and misspecification.

The individual and systemic risks of the banks have a time-varying component, depending on different risk factors that affect the banking sector. Adrian and Brunnermeier (2016) propose the estimation of VaR and CoVaR to be conditioned on several market indices that incorporate information representative for the global financial markets. Moreover, these indices are lagged one period in order to control for the speed of the adjustment:

$$M\boldsymbol{I}^{'}_{t-1} = (MI_{1,t-1}, \ldots, MI_{k,t-1}) \quad (3)$$

The market indices that we have used are presented in Appendix A.

Each bank's VaR is computed using a linear model that captures the dependence of bank's asset returns on vector $M\boldsymbol{I}^{'}_{t-1}$:

$$R^{i}_{Market\ Assets,t} = \alpha^{i} + \beta^{i} \times M\boldsymbol{I}^{'}_{t-1} + \varepsilon^{i} \quad (4)$$

where α^{i} is the constant (unobserved characteristics of bank *i*), β^{i} is a *(k × 1)* vector that captures the bank's *i* return dependence relationship with the market indices, and ε^i is an *iid* error term.

The return of the system can vary with each bank's return and with the lagged market indices as well:

$$R^{System}_{Market\ Assets,t} = \alpha^{System|i} + \delta^{System|i} \times R^i_{Market\ Assets,t} + M\boldsymbol{I}'_{t-1} \times \beta^{System|i} + \varepsilon_t^{System|i} \quad (5)$$

where $\alpha^{System|i}$ is the constant, capturing the banking system characteristics conditioned on bank *i*, $\beta^{System|i}$ is a *(k × 1)* vector of coefficients that captures the system's return dependence relationship with the lagged market indices, $\delta^{System|i}$ reflects the conditional dependence of the system's return on bank's *i* return, and $\varepsilon^{System|i}$ is the *iid* error term.

Running regression from Eq. (4) and Eq. (5) for a quantile of 5% (distressed periods) and a quantile of 50% (median or tranquil state) we obtain the value of regressors to be used in VaR and CoVaR estimations:

$$\widehat{VaR^i_{q,t}} = \widehat{\alpha^i_{q,}} + M\boldsymbol{I}'_{t-1} \times \widehat{\beta^i_q} \quad (6)$$

$$Co\widehat{VaR}^i_{q,t} = \alpha_q^{\widehat{System}|i} + \delta_q^{\widehat{System}|i} \times \widehat{VaR^i_{q,t}} + M\boldsymbol{I}'_{t-1} \times \beta_q^{\widehat{System}|i} \quad (7)$$

In the end, each financial institution's contribution to systemic risk (ΔCoVaR) is defined as the difference between VaR of the whole system conditioned on the event that the financial institutions registers the lowest return at a given confidence level and VaR of the whole system conditioned on the event that the financial institution faces the median return:

$$\Delta CoVaR^{System|i}_{q,t} = CoVaR_{q,t}^{System|R^i_{Market\ Assets}=VaR^i_{q,t}} - CoVaR_{q,t}^{System|R^i_{Market\ Assets=VaR^i_{50\%}}}$$

(8)

A greater value of ΔCoVaR is associated with an enhanced contribution to overall systemic distress.

Another systemic risk measure that we apply is Marginal Expected Shortfall (MES) of Acharya et al. (2017). It works in the opposite direction as compared with CoVaR, denoting the exposure of banks to systemic risk. MES is defined in Acharya et al. (2017) as the average return on bank's stock prices on the days the market experienced a loss greater than a specified threshold *C* indicative of market distress, which in our case is 5%:

$$MES_{t-1}^{i} = E_{t-1}(R_t^i | R_t^{System} < C) \tag{9}$$

where R_t^i is the return of bank *i* at time t and R_t^{System} is the return of the system, defined as the return of MSCI World Financial index. We model the bivariate process of firm and market returns as follows:

$$R_t^{System} = \sigma_t^{System} \varepsilon_t^{System} \tag{10}$$

$$R_t^i = \sigma_t^i \varepsilon_t^i = \sigma_t^i \rho_t^i \varepsilon_t^{System} + \sigma_t^i \sqrt{1 - \rho_{i,t}^2 \xi_{i,t}} \tag{11}$$

σ_t^i and σ_t^{System} are the volatilities of bank *i* and system, respectively, ρ_t^i is the correlation coefficient between the return of bank *i* and the return of the system, and ε_t^{System}, ε_t^i and $\xi_{i,t}$are the error terms which are assumed to be *iid.* It follows that:

$$MES_{t-1}^{i} = E_{t-1}\left(R_t^i \middle| R_t^{System} < C\right) = \sigma_t^i E_{t-1}(\varepsilon_t^i | \varepsilon_t^{System} < \frac{C}{\sigma_t^{System}}) =$$

$$\sigma_t^i \rho_{i,t} E_{t-1}(\varepsilon_t^i | \varepsilon_t^{System} < \frac{C}{\sigma_t^{System}}) + \sigma_t^i \sqrt{1 - \rho_{i,t}^2} E_{t-1}(\xi_t^i | \varepsilon_t^{System} < \frac{C}{\sigma_t^{System}}) \tag{12}$$

Conditional volatilities of the equity returns are modelled using asymmetric GJR-GARCH models with two steps Quasi Maximum Likelihood (QML) estimation, whilst time-varying conditional correlation is modelled using the Dynamic Conditional Correlation (DCC) framework of Engle (2002).

As in Benoit et al. (2014), we consider the threshold *C* equal to the conditional VaR of the system return, i.e., VaR (5%), which is common for all institutions. The higher the MES, the higher is the exposure of the bank to the systemic risk.

Since both ΔCoVaR and MES have a daily frequency, we convert them to median quarterly frequency and use it in the subsequent analysis.

2.2. Cycle extraction

In order to isolate the permanent component (trend) from the unobserved economic / financial cycle, i.e., our variable of interest, we employ a methodology widely used in macroeconomics time-series. This detrending algorithm was introduced by Hodrick and Prescott (1997), hence the HP filter, and addresses the Nelson and Plosser's (1982) argument that macroeconomic time series could be better characterized by stochastic trends than by linear trends. It decomposes a time-series y_t into a grow component (g_t) and an additive cyclical component (c_t). Rünstler and Vlekke (2018) argue that policymakers have to rely on past observations only because future values would not be available for real-time estimations (Stock and Watson, 1999). Thus, they point the necessity of one-sided filters.[10] Following Stock and Watson (1999), we estimate the one-sided HP filter using the Kalman filter.[11]

For GDP, from which we extract the economic cycle as in Drehmann et al. (2012), i.e., the output gap, we set the smoothing paramerter (λ) to 1,600. For the financial variables and domestic demand, the lambda is set to higher values to account for the fact that the frequency of financial cycle is higher than in the case of business cycle. Therefore, a value of 100,000 for λ is set for credit-to-GDP, house prices, equity prices, and domestic demand, as in Alessi and Detken (2011). In the end, we construct a synthetic financial index to aggregate all cycles in a useful indicator that can be used as early warning to signal possible imbalances in the real economy and financial sector (e.g. English et al., 2005; Ng, 2011). We apply the Principal Component Analysis (PCA) technique to output gap, domestic demand gap (computed with a lambda of 100,000), credit-to-GDP and house prices gaps to extract the principal component that will be our financial cycle index that can explain a large proportion of the variance.[12] The reason for which we compute de gap for domestic demand at higher frequency than GDP is that domestic demand may be more driven by financial factors, such as the level of the credit in the economy and the house prices, than the GDP.

[10] Consider the following example. Let's say that one has a time-series that starts in 2000q1 and wants to extract the cycle for the period from 2005q1 to 2017q4. Applying the one-sided HP filter, the cycle at 2005q1 is first calculated employing the data from 2000q1 to 2005q1, the cycle at 2005q2 is calculated from the data from 2000q1 to 2005q2, and so on so forth. In this case, when new data is released for 2018q1, the cycle and trend calculations are not altered as long as the past data is not revised. With the two-sided HP filter, however, the cycle is calculated using the entire time-series, and when new data is available, the past trend and cycles values have to be replaced with the new ones because of the change in the length of the time-series. Therefore, the one-sided HP filter is more robust comparing to its two-sided analogue.

[11] While the Kalman filter estimates give the one-sided HP filter, the Kalman smoother estimates give the two-sided HP filter (see Hamilton, 2017).

[12] We apply the PCA to demeaned data and pick only the first principal component, which is our synthetic index.

2.3. Econometric framework

Our dataset comprises banks from different countries for a period of 72 quarters, having thus a multi-level structure: banks are nested in countries. We employ a Hierarchical Linear Modeling (HLM) approach, which takes into consideration the fact that the data has different levels of aggregation and control for potential dependency due to nesting effects (Doumpos et al., 2015). Moreover, the model runs simultaneously at the country- and bank-level, and considers that the banks from a particular country are more similar to one another than banks from other countries. Also, the HLM comes in handy in explaining the variance at all levels of aggregation. Because the banking systems from different countries are inherently different, this issue can be captured by the HLM approach, being thus superior to standard OLS regression. This approach has been recently used in cross-country studies that examine firm performance, capital structure decisions, corporate risk-taking, and IPOs (Kayo and Kimura, 2011) or bank soundness (Doumpos et al., 2015).

The model has the following form:

$$SR_{ij,t} = \underbrace{\alpha_0 + \alpha_1 \times Cycle_{j,t-1} + \gamma \times \boldsymbol{X}_{ij,t-1} + \delta \times \boldsymbol{Z}_{j,t-1}}_{fixed\ components} + \underbrace{u_{ij} + e_j + \varepsilon_{ij,t}}_{random\ components} \quad (13)$$

where $SR_{ij,t}$ is the systemic risk measure of bank *i* from country *j* (ΔCoVaR and MES), $Cycle_{j,t-1}$ is the main variable of interest which quantifies business and financial cycles in quarter *t-1*[13], $\boldsymbol{X}_{ij,t-1}$ is a $(k \times 1)$ vector of lagged bank-level control variables (i.e., size, equity/total assets - capitalization, return on equity - profitabiity, deposits/total liabilities – funding structure, net loans/total assets – lending activities, loan loss provisions/total assets – credit risk, and non-interest income/total revenues – income diversification) and $\boldsymbol{Z}_{j,t-1}$ is a $(k \times 1)$ vector of banking system (i.e., the assets of the three largest commercial banks as a share of total commercial banking assets - concentration) and country-level control variables (i.e., capital account openness – financial liberralization, economic freedom, and inflation) in quarter *t-1*. The random variables u_{ij} and e_j allow the intercept ($\alpha_0 + u_{ij} + e_j$) to be random and unique to every bank and country. $\varepsilon_{ij,t}$ is the error term. The model depicted in Eq. (13) assumes that the intercept is random whereas the slopes are fixed. The model

[13] In an alternative specification, we include in Eq. (13) all independent variables with a lag of four.

is fit using the maximum likelihood estimation (ML) of the variance components of Hartley and Rao (1967). We use lagged independent variables in order to control for the speed of adjustment of systemic risk indicators as well as to control for any reverse causality problems (Anginer et al., 2014).To mitigate the problem of outliers, we winsorize all variables within the 1% and 99% percentiles.

3. Empirical results

3.1. Descriptive statistics

Table 1 provides summary statistics for the variables used in our empirical analysis mentioned in the Section 2.3. In terms of contribution to systemic risk, ∆CoVaR shows a mean of 0.36% with a standard deviation of 0.49%, while MES, which denotes exposure of banks to systemic stress, has an average of 0.99% with a standard deviation of 1.07%.

Table 1.
Summary statistics of regression variables.

	Mean	St. Dev.	Median	Min	Max	Obs.
∆CoVaR	0.3517	0.4901	0.2538	-1.0884	24.3369	30675
MES	0.9870	1.0657	0.7401	-2.678	12.2846	30674
Output gap	0.0768	1.4623	0.2826	-17.0452	23.9289	30675
Credit-to-GDP gap	-1.8675	5.4124	-0.6778	-40.219	23.9351	30309
House prices gap	-3.5173	9.5238	-0.0001	-42.8415	24.9509	30367
Equity prices gap	6.7177	23.6148	10.6439	-338.0185	121.6665	30675
Financial cycle index	-0.0435	0.5152	0.0667	-2.9399	2.3912	30001
Size	22.0242	2.0258	21.51	17.096	28.9227	29160
Capitalization	19.3834	9.7830	17.0731	-142.6945	99.7423	28725
Profitability	0.0298	4.9155	0.0921	-616.5357	44.8983	28918
Funding structure	79.812	16.2657	84.5787	-0.0223	104.5765	29128
Lending activities	66.6953	12.7067	67.9374	-1.3862	170.4166	29132
Credit risk	0.1371	1.5384	0.0501	-3.0352	166.8618	28719
Income diversification	18.7299	115.0263	18.1021	-18856.1200	671.4130	29077
Bank concentration	42.6357	19.9073	35.1331	21.3068	121.8514	30075
Financial openness	1.7489	1.0967	1.5860	-0.4541	4.0584	30075
Economic freedom	75.7654	5.418	77.1109	50.5085	83.0809	30675
Inflation	2.1276	1.5591	2.0865	-4.7089	53.5725	30675

Note: A complete description of the variables and data sources is given in Appendix A. All variables with the exception of cycle indicators, *Financial openness* and *Economic freedom* are expressed in percentage.
Bank-specific balance sheet, banking system and macroeconomic variables statistics are based on regression with output gap as the main regressor.
The minimum figure for *Income diversification* corresponds to Kredyt Bank from Poland for 2009q4. To minimize the impact of outliers, we winsorize all variables within the 1% and 99% percentiles.

Moving to cycles variables, we can note that with the exception of output and equity prices gaps, all the others gaps have a negative mean. i.e., on average, for the 36 countries from our sample, the deviation from the trend over 2000q1-2017q4 period was downwards. Negative values for gaps indicate that economic and financial sectors function below their potential, and are associated with difficult periods.

3.2. Baseline results

Table 2 summarizes the results of estimating Eq. (13) for the influence of business and financial cycles on systemic risk contribution, ΔCoVaR, is defined by Adrian and Brunnermeier (2016). This measure captures the spillover effects from each bank to the banking system. We assume a lag of one quarter to control for the speed of adjustment of systemic risk to macroeconomic and financial factors.[14] The estimated coefficients of output gap[15] (Model 1), house and equity prices gaps (Mode 3 and 4, respectively) and financial cycle index (Model 5) are positive and statistically significant, demonstrating that banks' systemic risk contribution fluctuates procyclically over the course of business and financial cycles.[16] In other words, when the gap between the actual variable and its long-run trend increases – typically periods associated with booms when credit and asset prices grow rapidly, lending spreads are reduced, banks hold low capital buffers and provisions and there is over-optimism among market participants – systemic risk accumulates excessively in the banking sector as financial imbalances develop. Thus, ΔCoVaR satisfies the viewpoint of Borio et al. (2001) who sees risk as rising in booms, not in downturns, and the aftermath of the crisis being just the consequence of risk materialization in the expansion phase. However, in the case of credit cycle (Model 2), although positive, the relationship turns out to be statistically insignificant. This finding is to some extent in line with IMF's (2002) study which concludes that since 1970's two thirds of credit booms did not terminate with a financial crisis. Therefore, if lending

[14] The findings remain robust after employing four lags. The output is available upon request.
[15] We obtain similar results employing Kamber et al.'s (2017) methodology for output gap.
[16] Other studies (e.g., BCBSa, 2010; Drehmann et al., 2012) use a smoothing parameter of 400,000 in order to extract financial cycles. Our results remain robust for both systemic risk contribution and exposure after employing the one-sided HP filter with lambda set at 400,000.

Table 2.
Estimation results for contribution to systemic risk.

Dependent: ∆CoVaR	(1)	(2)	(3)	(4)	(5)
Fixed-effects parameters					
Output gap (t-1)	0.0064***				
	(0.0011)				
Credit-to-GDP gap (t-1)		0.0003			
		(0.0002)			
House prices gap (t-1)			0.0014***		
			(0.0002)		
Equity prices gap (t-1)				0.0008***	
				(0.0001)	
Financial cycle index (t-1)					0.0068***
					(0.0022)
Size (t-1)	0.0198***	0.0192***	0.0159***	0.0195***	0.0176***
	(0.0024)	(0.0024)	(0.0024)	(0.0024)	(0.0024)
Capitalization (t-1)	-0.0005***	-0.0005***	-0.0004***	-0.0005***	-0.0005***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Profitability (t-1)	0.0012	0.0025	-0.0007	-0.0051	0.0013
	(0.0081)	(0.0081)	(0.0082)	(0.0081)	(0.0082)
Funding structure (t-1)	-0.0003***	-0.0003***	-0.0003***	-0.0004***	-0.0004***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Lending (t-1)	-0.0001	-0.0002*	-0.0002**	-0.0001	-0.0002*
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Credit risk (t-1)	0.0430***	0.0427***	0.0490***	0.0437***	0.0440***
	(0.0049)	(0.0050)	(0.0051)	(0.0049)	(0.0050)
Income diversification (t-1)	-0.0004***	-0.0004***	-0.0004***	-0.0004***	-0.0004***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Bank concentration (t-1)	0.0003*	0.0003	0.0005***	0.0001	0.0003
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Financial openness (t-1)	0.0064***	0.0074***	0.0101***	0.0077***	0.0084***
	(0.0015)	(0.0016)	(0.0016)	(0.0015)	(0.0016)
Economic freedom (t-1)	-0.0008	-0.0015***	-0.0002	0.0013**	-0.0008
	(0.0005)	(0.0005)	(0.0006)	(0.0006)	(0.0006)
Inflation (t-1)	0.0025**	-0.0002	-0.0006	0.0030**	0.0013
	(0.0012)	(0.0013)	(0.0012)	(0.0012)	(0.0013)
Constant	0.1184	0.1885**	0.1579*	0.0065	0.1737**
	(0.0813)	(0.0810)	(0.0834)	(0.0816)	(0.0840)
Random-effects parameters					
Country-level variance	-1.5284***	-1.5137***	-1.5139***	-1.5592***	-1.5158***
	(0.1642)	(0.1628)	(0.1635)	(0.1669)	(0.1637)
Bank-level variance	-1.3403***	-1.3392***	-1.3300***	-1.3395***	-1.3362***
	(0.0274)	(0.0275)	(0.0275)	(0.0274)	(0.0275)
Residual variance	-2.2102***	-2.2095***	-2.2113***	-2.2115***	-2.2102***
	(0.0041)	(0.0041)	(0.0041)	(0.0041)	(0.0041)
Quarterly observations	30675	30663	30367	30675	30355
Countries	36	36	36	36	36
Banks	789	789	789	789	789
LR-test chi-square	46325***	46322***	45941***	46299***	45734***

Note: This table reports the results for the model described in Eq. (13). The dependent variable is ∆CoVaR, defined in Appendix A. The HML model is estimated using the maximum likelihood estimation. The LR test compares the estimated model with the standard OLS regression, and the null is that there are no significant differences between the two models. Standard errors in parentheses,
***, **, and * denote statistical significance at 1%, 5% and 10%, respectively.

Table 3.
Estimation results for exposure to systemic risk.

Dependent: MES	(1)	(2)	(3)	(4)	(5)
Fixed-effects parameters					
Output gap (t-1)	0.0078**				
	(0.0036)				
Credit-to-GDP gap (t-1)		0.0131***			
		(0.0008)			
House prices gap (t-1)			0.0123***		
			(0.0006)		
Equity prices gap (t-1)				-0.0021***	
				(0.0002)	
Financial cycle index (t-1)					0.0081
					(0.0073)
Size (t-1)	0.1667***	0.1565***	0.1524***	0.1659***	0.1697***
	(0.0065)	(0.0065)	(0.0066)	(0.0065)	(0.0065)
Capitalization (t-1)	0.0004	0.0007	0.0009**	0.0005	0.0005
	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0005)
Profitability (t-1)	0.0602**	0.0356	0.0190	0.0842***	0.0549**
	(0.0274)	(0.0273)	(0.0273)	(0.0274)	(0.0276)
Funding structure (t-1)	0.0005	0.0010**	0.0008*	0.0007*	0.0004
	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)
Lending (t-1)	-0.0001	-0.0004	-0.0004	-0.0002	0.0001
	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)
Credit risk (t-1)	0.0976***	0.1288***	0.1509***	0.0915***	0.0928***
	(0.0166)	(0.0167)	(0.0170)	(0.0166)	(0.0169)
Income diversification (t-1)	-0.0006**	-0.0005*	-0.0006**	-0.0005*	-0.0007**
	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)
Bank concentration (t-1)	-0.0031***	-0.0017***	-0.0003	-0.0028***	-0.0023***
	(0.0006)	(0.0006)	(0.0006)	(0.0006)	(0.0006)
Financial openness (t-1)	-0.0288***	-0.0090*	0.0011	-0.0305***	-0.0219***
	(0.0051)	(0.0052)	(0.0053)	(0.0051)	(0.0052)
Economic freedom (t-1)	-0.0134***	-0.0142***	0.0027	-0.0215***	-0.0087***
	(0.0018)	(0.0017)	(0.0020)	(0.0019)	(0.0021)
Inflation (t-1)	0.0221***	-0.0094**	0.0088**	0.0130***	0.0193***
	(0.0042)	(0.0044)	(0.0041)	(0.0041)	(0.0043)
Constant	-1.8195***	-1.5574***	-2.7740***	-1.2943***	-2.2501***
	(0.2176)	(0.2168)	(0.2267)	(0.2223)	(0.2265)
Random-effects parameters					
Country-level variance	-1.0944***	-1.0189***	-0.9792***	-1.0392***	-1.1041***
	(0.1568)	(0.1527)	(0.1495)	(0.1548)	(0.1567)
Bank-level variance	-0.9112***	-0.8966***	-0.8918***	-0.9112***	-0.9189***
	(0.0296)	(0.0300)	(0.0303)	(0.0297)	(0.0297)
Residual variance	-0.9915***	-0.9966***	-1.0029***	-0.9926***	-0.9950***
	(0.0041)	(0.0041)	(0.0041)	(0.0041)	(0.0041)
Quarterly observations	30674	30662	30366	30674	30354
Countries	36	36	36	36	36
Banks	789	789	789	789	789
LR-test chi-square	21146***	21459***	21482***	21128***	20706***

Note: This table reports the results for the model described in Eq. (13). The dependent variable is MES, defined in Appendix A. The HML model is estimated using the maximum likelihood estimation. The LR test compares the estimated model with the standard OLS regression, and the null is that there are no significant differences between the two models. Standard errors in parentheses,
***, **, and * denote statistical significance at 1%, 5% and 10%, respectively.

booms are demand-driven and are based on sound microeconomic fundamentals, they could be harmless to systemic risk (Peydró, 2013).

In terms of exposure to systemic banking risk that we proxy by MES, defined as the average return on banks' stock prices on the days the MSCI World Financial index experienced its 5% worst outcomes, we document similar findings to ∆CoVaR, however, with some relevant differences (Table 3). The GDP gap, credit-to-GDP gap and house prices gap have a positive influence on MES, and hence, banks' systemic risk exposure is procyclical in terms of economic, credit and house cycles. The main difference stems from credit and equity cycles. Here, the credit cycle appears to have a direct link with exposure to systemic banking distress, i.e., banks behave procyclically during credit cycles when they are exposed to a common source of systemic stress coming from financial system as a whole.When it comes to equity cycle, the results provide evidence of a negative association with exposure to systemic risk, i.e., MES evolves in an counterciclycal manner during the equity cycles.

Turning to control variables analysis, the empirical investigation yields results that are in most of the cases in line with our ex-ante beliefs. As expected, the sign of *Size* is positive and the variable is statistically significant at 1% in all ten models outlined in Table 2 and Table 3, consistent with Laeven et al. (2016). This indicates that larger banks tend to engage in activities that are too risky, since they are more diversified and have easier access to the capital markets than their smaller counterparts do. Also, this seems to confirm the too-big-to-fail hypothesis, larger banks being susceptible to be bailed-out by government in the event of financial distress, thus having more incentives of excessive risk-taking behavior and thus increase overall systemic risk in the financial sector. *Capitalization*, defined as the ratio of total capital to total assets, is a significant determinant only for contribution to systemic risk, with a negative impact. Hence, banks can finance themselves in difficult times when the funding costs are considerable higher and thus have a greater flexibility to respond to adverse shocks and absorb more losses. *Profitability*, proxied by ROE, is not significant in the case of ∆CoVaR, but turns out to be significantly positive in the case of MES, in Model 1 and Model 4, which contradicts our prior expectations. In terms of *Funding structure*, computed as total deposits in total liabilities, the findings are mixed. We document that higher level of deposits reduce banks' systemic risk contribution since during financial distress these funds are less likely to be withdrawn than non-deposit funds, whereas the association with exposure to systemic risk is positive in two models.

Further, we find that banks that hold large portfolios of loans as ratio of total assets (*Lending activities*) contribute less to system-wide distress only in association with house and credit cycles, and financial cycle index. For the rest of models, the coefficients are undistinguishable from zero.

Moving to *Credit risk* variable computed as loan loss provisions over total assets, empirical evidence confirms our ex-ante expectations: increased levels of funds that are budgeted by the banks as a result of uncollectable or troubled loans, being thus an indicator of the quality of their loan portfolios, are associated with enhanced contribution and exposure of banks to systemic risk.

The coefficients of *Income diversification* are negative and highly significant for both ∆CoVaR and MES, indicating that diversification benefits exist. Our findings could be linked to Stiroh and Rumble's (2006) and Laeven and Levine's (2007) arguments of risk-reducing due to portfolio diversification benefits. Also, income diversification might provide effective hedges against risks from loan portfolio quality (Shim, 2013).

The results of other control variables are generally consistent with our hypotheses. *Bank concentration* (assets of the three largest commercial banks as a share of total commercial banking assets) has a negative impact on banks' exposure to systemic distress across all models, whereas the coefficients' sign in the case of ∆CoVaR is positive and significant in Models 1 and 3, and insignificant for the rest of the models. The estimated coefficients of *Financial openness* (or capital account openness) differ across ∆CoVaR and MES, and are highly significant at 1% level. In terms of systemic risk exposure, the sign of capital account openness variable is negative, being consistent with Bostandzic and Weiß (2018). However, the contribution of banks to systemic risk seems to enhance with a more capital account openness due to volatile capital flows that enter the countries. *Economic freedom*, as expected, in most of the cases leads to a decrease in the overall systemic risk level in banking sector, whereas *Inflation* amplifies it.

In summary, we find that economic cycles, house cycles and financial cycle index are positively and significant related to banks' systemic risk contribution and exposure, meaning that ∆CoVaR and MES are procyclical in relation to business and house cycles, and the accumulation of systemic risk in the banking sector is at its highest during economic and house booms. When it comes to excessive credit growth that is often cited as the main trigger of banking crises, we document that contribution and exposure to systemic risk evolves procyclically during credit cycles, but in the case of the former, the relationship is not statistically significant. Finally, ∆CoVaR exhibits a procyclical pattern during equity cycles, whereas for MES is the other way around.

4. Robustness checks

Hamilton (2017) argues that one should never use the Hodrick-Prescott because it produces series with spurious dynamic relations, the end-points are very different from those in the middle, and it typically produces values for the smoothing parameter that are at odds with its statistical foundations.[17] He proposes an alternative based on linear projections that should overcome these drawbacks. More precisely, he suggests the estimation of the following equation:

$$y_{t+h} = \beta_0 + \beta_1 y_t + \beta_2 y_{t-1} + \beta_3 y_{t-2} + \beta_4 y_{t-3} + \vartheta_{t+h} \quad (14)$$

For business cycles, the author recommends h=2 years and four lags, while for applications to debt cycles, h=5 years may be appropriate. Thus, we set h=8 quarters for GDP, and h=20 quarters for financial variables (for financial cycles extraction). In the end, the gap is given by the expression below:

$$projection\ gap = \vartheta_{t+h} \quad (15)$$

To conserve space, the results employing Hamilton's technique for ∆CoVaR and MES, respectively are not shown, but are available upon request. Overall, there are no significant differences comparing to one-sided HP filter. In the case of systemic risk contribution, however, this time the influence of output gap is not significant. Moreover, the coefficient of credit-to-GDP gap is positive and highly

[17] Hodrick-Prescott filter is suggested by Basel III in setting countercyclical capital buffers, and it's used by the BIS. Drehman and Yetman (2018) address Hamilton's (2017) criticisms and find that credit-to-GDP gap from one-sided HP filter, a method firstly proposed by Borio and Lowe (2002), outperforms other cycle extraction methods, including the linear projection proposed by Hamilton (2017).

significant, which is consistent to some extent with the findings from HP filter (Table 2, Model 2). For systemic risk exposure, the main difference is for equity cycle, which appears to have a positive and significant link with MES at 1% level. Because of these contradictory findings, we employ a third method, i.e., we use a 12-quarter backward moving average as a trend similar to Ito et al. (2014) who use a 3-year moving average, and the cycle is computed as the actual variable minus the trend. We obtain a similar outcome as in the case of HP filter, and thus we made the inference based on HP filter methodology.

5. Conclusion

One of the upshots of the recent global financial crisis is that the microprudential supervision performs poorly and does not take into account the spillover effects between financial institutions. The macroprudential paradigm established under Basel III is believed to overcome these shortcomings and keep under control systemic riskiness in the banking sector. But how banks' systemic risk contribution and exposure fluctuate over the course of business and financial cycles? Are they procyclical or countercyclical in nature?

Using a sample of 789 banks from OECD and EU-28 countries, we document that both systemic risk contribution and exposure are positively related to business cycle. That is, systemic risk starts to accumulate in the financial sector during periods of boom, i.e., when output gap is positive. Furthermore, during periods of robust economic growth, the level of credit tends to increase dramatically, going hand in hand with asset and property prices developments. These variables are associated with financial cycles and their behavior amplifies the economic cycle which can result, under certain conditions, in a financial crisis. We find that contribution to system-wide distress moves procyclically during credit, house and equity cycles, but the results are not significant for credit cycles. As Peydró (2013) points-out, if credit expansion has economic fundamentals and is demand-driven, it could be harmless for systemic risk. In terms of banks' exposure to systemic distress, it evolves procyclically during credit and house cycles, and counterciclycally during equity cycles. Our index of financial cycle constructed using both macroeconomic and financial variables confirms the pattern of systemic risk to evolve procyclically. Additionally, the empirical analysis shows that both bank-specific and macroeconomic factors influence banks' systemic stress. Particularly, size, loan loss provisions and inflation positively affect systemic risk contribution and exposure of the banks, whereas capitalization, the share of loans in total assets, the share of non-interest income in total revenue, financial openness and financial freedom help banks in reducing their systemic importance. The results remain robust after controlling for nesting and possible reverse causality issues, and after employing different techniques for separating cycles from the trend.

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Appendix A.
Description of variables.

Variable name	Definition	Source
Dependent variables (bank-level)		
Contribution to systemic risk (ΔCoVaR)	Bank i's quarterly contribution to systemic risk as defined by Adrian and Brunnermeier (2016). It is measured as the difference of the Value-at-Risk (VaR) of the system's market value of total assets conditional on the distress of a particular bank (5% worst outcomes) and the VaR of the system's market value of total assets conditional on the median state of the bank (median outcomes). ΔCoVaR is estimated using the Quantile Regression method for an empirical specification where the system's market value of total assets is regressed on each banks' market value of total assets and on a set of market indices that captures the exposure of financial institutions to common factors. The common factors are: (i) the daily return of MSCI World index, (ii) the volatility index (VIX), (iii) the daily real estate sector return (MSCI World Real Estate) in excess of the financial sector return (MSCI World Financials), (iv) the change in the three-month T-bill rate, (v) the change in TED spread rate, (vi) the change in spread between Moody's Baa-rated bonds and the ten-year Treasury rate and (vii) the change in the slope of the yield curve, measured by the spread between the composite long-term bond yield and the three-month T-bill rate. System is defined as the market value of total assets of the sample.	Own calculations
Marginal Expected Shortfall (MES)	Quarterly Marginal Expected Shortfall as defined by Acharya et al. (2017) as the average return on an individual bank's stock on the days the MSCI World Financial experienced its 5% worst outcomes. Conditional volatilities of the equity returns are modelled using asymmetric GJR-GARCH models with two steps Quasi Maximum Likelihood (QML) estimation, whilst time-varying conditional correlation is modelled using the Dynamic Conditional Correlation (DCC) framework of Engle (2002).	Own calculations
Cycle indicators (country-level)		
Output gap	Proxy for business cycle. The cycle has been extracted based on real and seasonally adjusted GDP, computed as an index, 2010q4=100, using a smoothing parameter of 1,600 with one-sided Hodrick-Prescott filter.	World Bank; Own calculations
Credit-to-GDP gap	Proxy for credit cycle (financial cycle). Banking credit-to-GDP ratios have been converted to quarterly frequency using cubic spline interpolation from annual data. The cycle has been extracted based on credit-to-GDP ratio, computed as an index, 2010q4=100, using a smoothing parameter of 100,000 with one-sided Hodrick-Prescott filter. The data for Canada is only available until 2008, so we use the ratio of domestic credit to private non-financial sector from Bank for International Settlements (BIS).	World Development Indicators (WDI); Bank for International Settlements (BIS); Own calculations
House prices gap	Proxy for house cycle (financial cycle). The cycle has been extracted based on real and seasonally adjusted house prices index, 2010q4=100, using a smoothing parameter of 100,000 with one-sided Hodrick-Prescott filter.	Eurostat; Oxford Economics; OECD; Own calculations
Equity prices gap	Proxy for equity cycles (financial cycle). The cycle has been extracted based on real and seasonally adjusted equity prices index, 2010q4=100, using a smoothing parameter of 100,000 with one-sided Hodrick-Prescott filter.	Datastream; Own calculations
Financial cycle index	Index calculated using Principal Component Analysis (PCA) from the principal component from the following variables: output gap, domestic demand, computed with a smoothing parameter of 100,000, credit-to-GDP gap, and house prices gap.	Oxford Economics; OECD; Own calculations
Data used for systemic risk (bank-level)		
Market equity	Market capitalization	Datastream
Total assets	Book value of total assets	Worldscope

Book equity	The book value of common equity	Worldscope
Market assets	Total assets × (Market equity/Book equity)	Own calculations
Bank-level control variables		
Size	Natural logarithm of total assets	Worldscope
Capitalization	Total capital/Total assets. Total capital includes common equity, minority interest, long-term debt, non-equity reserves and deferred tax liability in untaxed reserves.	Worldscope
Profitability (ROE)	Net income/Common equity	Worldscope
Funding structure	Total deposits/Total liabilities	Worldscope
Lending	Net loans/Total assets	Worldscope
Credit risk ratio	Loan loss provisions/Total assets	Worldscope
Income diversification	Non-interest income/Total revenue	Worldscope
Macro/banking-system level control variables		
Bank concentration	Assets of three largest banks as a share of total commercial banking assets. Total assets include total earning assets, cash and due from banks, foreclosed real estate, fixed assets, goodwill, other intangibles, current tax assets, deferred tax, discontinued operations and other assets. Data has been converted to quarterly frequency using cubic spline interpolation from annual data.	World Development Indicators (WDI)
Financial openness	Financial openness index is defined as the degree of capital account openness. A higher index value implies more open a particular country is to cross-border capital transactions. Data has been converted to quarterly frequency using cubic spline interpolation from annual data.	Chinn and Ito (2008)
Economic freedom	Economic freedom index is based on 12 quantitative and qualitative factors, grouped into four broad categories, or pillars, of economic freedom: (i) rule of law (property rights, government integrity, judicial effectiveness), (ii) government size (government spending, tax burden, fiscal health), (iii) regulatory efficiency (business freedom, labor freedom, monetary freedom), and (iv) open markets (trade freedom, investment freedom, financial freedom). A higher index value implies higher degree of economic freedom. Data has been converted to quarterly frequency using cubic spline interpolation from annual data.	Heritage Foundation
Inflation	Inflation is measured by the consumer price index and reflects the annual percentage change in the cost to the average consumer of acquiring a basket of goods and services that may be fixed or changed at specified intervals. Data has been converted to quarterly frequency using cubic spline interpolation from annual data.	World Development Indicators (WDI)

Poverty and inequality in Romania: an overview after a decade of EU membership[1]

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„The bitter-sweet reality is that despite economic growth there are still far too many people who are left out” - Christine Lagarde

Abstract:

Although Romania has enjoyed strong economic performance over the last years, raising citizens` income towards those in Western European countries, the quality of growth is undermined by regional disparities, high level of income inequality and poverty rate. Strong growth has lifted a large part of the population out of poverty, but there is still ample room for improvement.

The objective of this paper is twofold: (i) to highlight the state of play and the evolution of poverty and income inequality in Romania since the adhesion to the European Union and (ii) to suggest some policy implications and tentatively draft policy recommendations.

Since the income inequality has followed an unstable path, is fundamental for policymakers to better understand the main determinants of inequality in order to implement well-designed policies with positive distributional impact. Furthermore, given the sensitivity of social issues in Romania, when addressing specific problems, policymakers should have in mind the aim of reducing income inequality and poverty rate.

Key words: income inequality, poverty rate, Romania

[1] This paper was prepared for Costin Murgescu Contest (FGDB) and it contains 15 pages, including first page and references.

1. Short literature review on income inequality and poverty

High income inequality and still persistent poverty are considered critical current social and economic issues. Influential economists have pointed out that income inequality and poverty have negative macroeconomic consequences (Stiglitz, 2012; Milanovic, 2016; Piketty, 2014). Assessing and understanding the drivers and consequences of inequality is not a recent concern for economists, social issues being in the spotlight for centuries (Rousseau, 2017). In the aftermath of the global financial crisis, income inequality and poverty went on top of political and economic debates since there is an increasing evidence that the rise in economic and social inequality has played a major role for populism and political polarization (Fratzscher, 2018). Although there is still ample room for improvement, the standard of leaving has been remarkably improved over the last decades and nowadays the world is a better place than it used to be, with healthier and wealthier people (Deaton, 2013).

Inequality and poverty are multifaceted and complex concepts. Inequality captures how different incomes are for better, average and worse-off households, while the poverty rate captures how many households have income levels that fall below a certain threshold. This article is focusing on income inequality and poverty. However, in order to have a complete picture, other aspects should be taken into consideration, such as wealth and opportunities. Actually, wealth is more concentrated at the top of the distribution than income, but data on wealth inequality is scarce, so it is difficult to include such aspects in our analysis.

Persistently high rates of income inequality and poverty are widespread concerns. While some degree of inequality is treated as inevitable in a market-based economic system, even desirable, excessive inequality can lower economic growth, erode social cohesion and lead to political polarization (IMF, 2019). Tackling income inequality - across people, regions and groups - is critical for achieving strong, sustainable, balanced and inclusive growth. Furthermore, high and rising inequality has been negatively associated with growth and macroeconomic stability (IMF, 2014). International organization, such as the IMF, OECD, World Bank and European Commission strive to better understand the main drivers and to come out with appropriate policy recommendations.

A new face of income inequality. The approach regarding income inequality has changed over time. Considered previously as a necessary trade-off for achieving greater economic growth and causing very limited economic and social damage, a high level of income inequality is nowadays seen as a major threat to prosperity and human development. In addition, high inequality has many adverse consequences (Fratzscher, 2018), such as: (i) raising the poverty rate, in particular among children and retired people, (ii) reducing social and political participation which, at the end of the day weaken the functioning of democracy, (iii) increasingly depriving individuals to be independent and rely on their own savings.

Income inequality makes growth more fragile. There is growing evidence that economic growth and social inclusion do not always go together, and the lack of inclusion can be macroeconomically harmful. Income inequality increased in good times, but also in bad times. There are uneven views regarding the relationship between income inequality and economic growth. On the one hand, there are economists who argue that a higher degree of income inequality retards economic growth by diminishing investment in both human and physical capital, two main sources of long-term growth (IMF, 2019). Contrariwise, others have seen income inequality as a deserved outcome of the rewards to innovation and risk-taking. Although a certain level of inequality can be socially acceptable, it is extremely difficult to define a precise threshold above which income inequality starts having harmful effects.

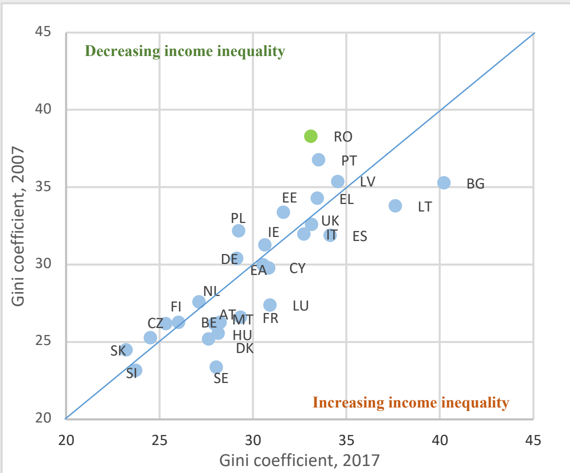
Despite European Union`s efforts in achieving economic, social and territorial cohesion, the EU is still characterised by high heterogeneity among Member States. Poverty reduction is included in the Europe 2020 Strategy and it is considered a key policy component. At the EU level, the highest income inequality and poverty rate is observed in Romania, Bulgaria, Spain, Latvia and Greece. Over the last decade, the changing in inequality and poverty rate show a diverging trend. Worse-off households from most vulnerable countries to global financial crisis are still struggling to achieve pre-crisis income levels.

There is a widespread literature on income inequality drivers. Economic theory suggest an extensive list of potential drivers, such as: quality of institutions (Acemoglu and Robinson, 2013), geography (Landes, 1999), technological progress (Acemoglu, 2003), demographics (European Commission, 2013), trade and financial openness (Furceri et al., 2018), structural reforms (European Commission, 2017; OECD, 2015; Ostry et al., 2018), fiscal policy (IMF, 2014), monetary policy (ECB, 2018), the size of government spending on education and healthcare system (Doumbia and Kinda, 2019; Jianu, 2018).

2. An overview of inequality and poverty in Romania – state of play and trends over the last decade

Despite some progress achieved over the last decade, Romania continues to be an unequal place and the level of inequality is still high by EU standards. When Romania joined the European Union in 2007, it registered the highest level of income inequality among all Member States. Over the last decade, limited progress has been achieved (income inequality as measured by Gini index[2] has decreased by 3.2 Gini points), but inequality continues to be a critical issue. This evolution can be partially explained by changes in fiscal and social policies. Similar results are found when using quintile share ratio as a measure of income inequality, one of the Social Scoreboard indicators. In 2018, the top 20% of the population with the highest income earned 7,2 times more income compared to the poorest 20%, the second largest disparity among EU Member States after Bulgaria (7,6).

Graph 1: Gini coefficient across EU MSs



Source: Eurostat, code ilc_di12

The evolution of income inequality has followed an unstable path over the last years. Income inequality reached a peak in 2007, but recorded a significant decrease in the following few years. However, in the aftermath of the crisis, Gini coefficient entered on a strong upward trend mainly due to a severe austere program adopted by the Romanian Government as a reaction to the global financial crisis. In 2016-2017, income inequality registered a substantial decline,

Graph 2: Gini coefficient trends

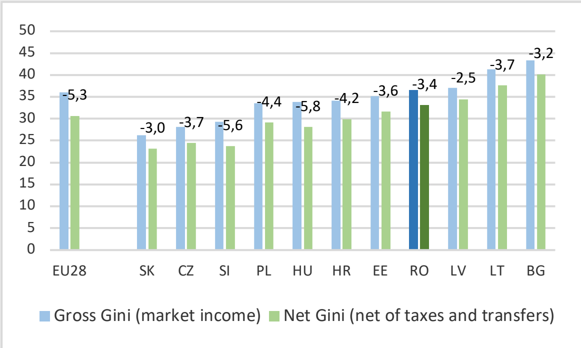
Source: Eurostat, code ilc_di12

[2] The Gini coefficient is the best-known measure of income distribution, based on surveys. It can take values from 0 to 1 (or 100), where 0 corresponds to a perfectly equal distribution (every household earn exactly the same income), and 1 express full inequality (situation where the whole income is earned by only one household). A lower value of Gini coefficient corresponds to a lower degree in income inequality.

followed by a new increase in 2018. Given this unstable path, it is fundamental for policymakers to better understand the main determinants of inequality, so they can implement well-designed policies with positive distributional effects.

The fiscal system has contributed to a reduction in inequality, but the redistributive impact of fiscal policies is more limited in Romania than in other EU Member States and well below the EU28 average. Since Romania has a relatively high level of inequality before taxes and transfers are taken into account (gross Gini), the more limited redistributive impact of fiscal policy means that inequality after taxes and transfers (net Gini) remains one of the highest in the EU. The combined effects of taxes and social spending help to reduce inequality, however there is ample room for improvement. Direct taxes and transfers are progressive and redistributive, but less so than in other peer countries (Hungary, Poland, Slovenia, Latvia, Croatia, the Czech Republic, etc.) On the other side, indirect taxes are regressive and aggravate inequality, reducing the overall redistributive impact of the tax system. For example, the decline in VAT rate has offered more benefits to richer households since they have greater purchasing power (Inchauste and Militaru, 2018).

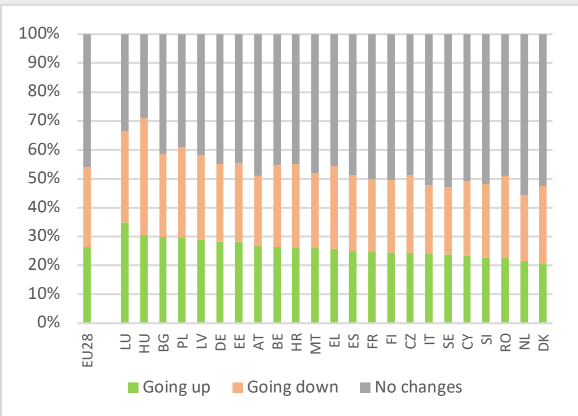
Graph 3: The redistributive impact of the fiscal system (pensions excluded from social transfers), 2017



Source : Eurostat, code ilc_di12; ilc_di12c

Social mobility is limited in Romania, only 23% of the population are going up to richer deciles. In the context of an inefficient social elevator, workers with potential talents are left behind, having very limited access to well-paid jobs. In the long run, low social mobility might undermine labour productivity and GDP growth. On the contrary, prospects of upward mobility have a strong positive influence on life satisfaction and well-being of citizens, while limited social mobility makes high degree of inequality socially less acceptable (OECD, 2018).

Graph 4: Social mobility, 2018

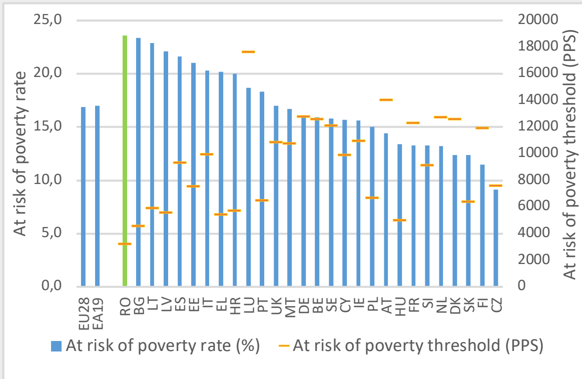


Source: Eurostat, code ilc_di30a

Poverty rate can be measured using different thresholds: i) \$5.5 a day (an international standard used by international organizations in upper-middle-income countries), ii) a threshold set at 60% of national median equivalised net income (used in general by the European Commission). For spatial comparison, thresholds are often expressed in purchasing power standards (PPS), in order to capture the cost-of-living differences across countries.

In relative terms, Romania's poverty level continues to be the highest in the European Union with 4.6 million of people at risk of poverty in 2017 (23.6%), and a slightly higher percentage for women (when considering a threshold of 60% of median equivalised net income). Although over the last decade the poverty rate has slightly decreased, poverty and social exclusion persist in particular for teenagers, people in the rural areas, families with children, people with disabilities, and those who are inactive (Inchauste and Militaru, 2018). Furthermore, in Romania, there are pregnant disparities associated with ethnicity. Beside this, Romania registered in 2017 the highest level of employed persons at risk of poverty after social transfers (13.3% compared to 7.7% the EU28 average) among EU Members States. In addition, more than 60% of part-time workers are at risk of poverty.

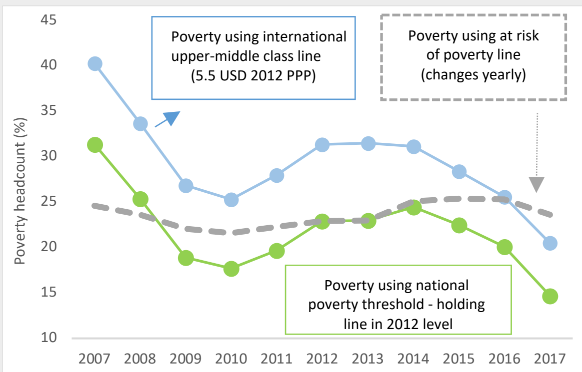
Graph 5: At risk of poverty rate[3] (after social transfer) and threshold, 2017



Source: Eurostat, code ilc_li02

Absolute poverty has halved between 2007 and 2017. By using the relative poverty line set at 60% of median incomes anchored at 2012 levels, poverty rate has decreased significantly in Romania. The finding of declining poverty comes from looking at how many people live in households with income levels per adult equivalent under RON 12 in 2012 prices – which is the 2012 at risk of poverty threshold. By using this approach, the number of people living at risk of poverty using the 2012 poverty line has

Graph 6: Evolution of poverty (using different poverty thresholds)



Source: World Bank

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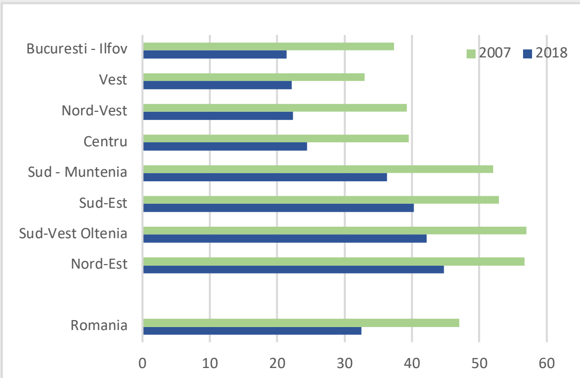
[3] At-risk-of-poverty threshold is set at 60% of national median equivalised disposable income after social transfers.

declined from 31% in 2007 to 15% in 2017 - green line. Similar results are found using international poverty line, translating into a decline of 3.9 million people living at risk of poverty between 2007 and 2017. Therefore, Romania has made remarkable progress in improving living conditions among low-income earners over the last decade. However, compared to peer countries, the situation is still very delicate, and the Government should intensify poverty reduction efforts. A particularity of the Romania`s situation is that poverty rate measured using the international threshold (5,5 USD in 2012 prices) is higher than poverty measured using the national threshold (60% of median income, prices anchored in 2012 prices), which highlights a more delicate situation compared to peer countries.

The share of people at risk of poverty or social exclusion has decreased significantly since the adhesion to the European Union (migration/demographic changes might have played a role). Despite the impressive and marked progress, in three NUTS2 regions more than 40% of the population are at risk of poverty or social exclusion, poverty being highly concentrated in rural areas. The graph below underlines in particular changes in the material deprivation since the relative poverty component has not shifted much.

Poor people are unequally distributed across NUTS2 regions. Despite notable improvement achieved by all Romanian NUTS2 regions in the catching-up process[4], several regions remain particularly exposed to poverty and social exclusion. This discrepancies across regions can be explained by high disparities in employment rate and productivity growth, the poorest regions being still based on subsistence agriculture. Furthermore, disparities in endowments (notably human capital) are significant. Economists underline a vicious cycle over time: a lack of access to quality education is both a consequence of today's income and wealth inequality and a cause of tomorrow's inequality (IMF, 2018).

Graph 7: People at risk of poverty or social exclusion[5] by NUTS2 regions



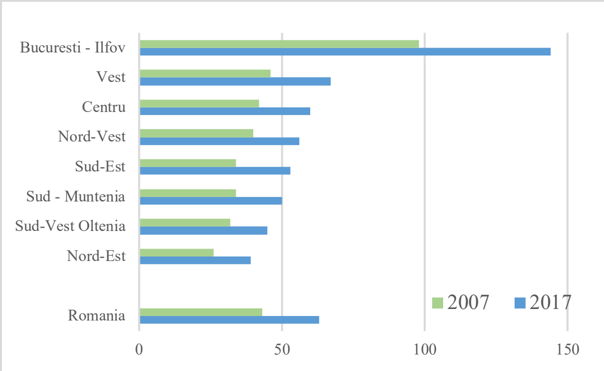
Source: Eurostat, code ilc_peps11

[4] According to the convergence theory, poorer regions/countries tend to grow faster than more robust regions/economies.
[5] According to Eurostat definition, this indicator corresponds to the sum of persons who are at least in one of the following situations: (i) at risk of poverty (below 60 % of the national median equivalised disposable income after social transfers), (ii) severely materially deprived or (iii) living in households with very low work intensity.

Romania is characterised by high regional disparities in terms of GDP per capita.

(big differences in living standards and opportunities depending on the place citizens live). While Bucharest - Ilfov is one of the richest regions of the European Union in terms of GDP per capita in purchasing power standard, all other regions registered a GDP per capita well below the EU28 average in 2017, with Nord-Est and Sud-Vest Oltenia still among the poorest European regions. In 2017, only three regions from Bulgaria were poorer than Nord-Est region. Overall, all Romanian regions have been converging since the EU accession, but at a very different speed, thus increasing the disparity between more and less developed regions. Disparities in productivity growth among regions have limited growth and convergence to EU average GDP per capita.

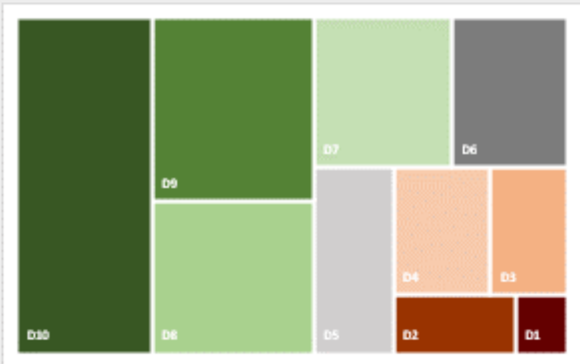
Graph 8: Regional GDP per capita in 2017 (% of EU28 average, PPS)



Source : Eurostat, code nama_10r_2gdp

In 2018 the 10th income decile, which accounts for the richest 10% of Romanian residents, captured a quarter of national income, almost the same amount as the poorest 50%, while the poorest decile earned only 1.7% of the national income. Poorest households have seen little improvements in households' income over the last decade, resulting in a declining share of their incomes. In 2018, the poorest 50% of the population earned just 27% of national income, while the richest decile has 23%. Therefore, over the last decade, top earners have benefitted much more than median or poor households.

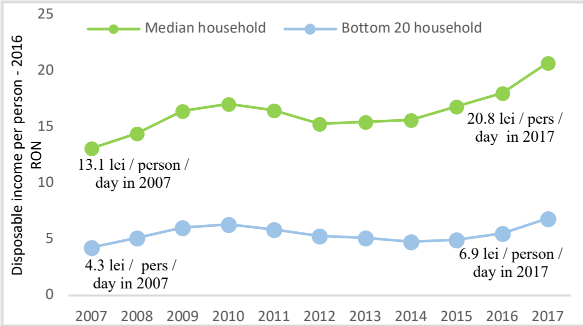
Graph 9: Share of national equivalised income by deciles, 2018



Source: Eurostat, code ilc_di01

Since 2007 median income and bottom 20 household's income per capita have expanded by ~60%. The standard of living for median and poorest households has improved over the last decade, but bottom 20 households still face critical challenges such as unequal access to education, health services or limited access to labour market. Despite this positive evolution, compared to other EU Member States, Romania registered the lowest median equivalised net income in 2017 (converted into purchasing power standard)[6].

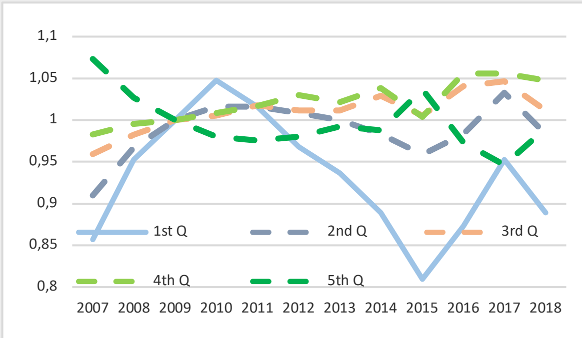
Graph 10: Median and bottom 20 households' income per capita



Source: World Bank

The poorest households were the most affected by the financial crisis. The drop in income suffered by the poorest 20 households was more profound and took longer to recover from. In the aftermath of the crisis, the Romanian social protection system was not sufficiently efficient in order to protect its citizens during periods of economic contraction. The austere program adopted by the Government in 2010 was among the most severe in the European Union, affecting in particular public employees[7] and social welfare beneficiaries (Stoiciu, 2012). The austerity measures had strong negative social consequences, as persistently high unemployment rate (mainly affecting low-skilled workers which are the most sensitive to business cycles), and increasing severe poverty. In good times, economic growth has not been fairly shared, while the economic crisis has only widespread the gap between poor and rich. While worse-off households experienced in general more economic volatility in several South-eastern and Central European countries (Bulgaria, Croatia, Cyprus, Italy, and Spain), some developed European countries managed to offer strong social protection to poorer households (Finland, France, Denmark, Belgium and Austria). It is important to underline that, in most vulnerable countries, both bottom 20

Graph 11: Income distribution per quintile (share of national income, 2009=100)



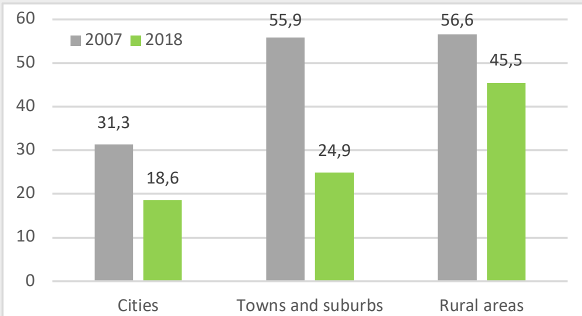
Source: Eurostat, code ilc_di01

[6] Median equivalised net income is a common indicator used as a measure to compare standards of living.
[7] In June 2010, the Government adopted a particularly severe austerity package, including: (i) cutting the government employees' wages by 25%, (ii) cutting social security benefits by 15%, (iii) increasing the value added tax by 5 percentage points, from 19% to 24%.

households' income and median income were in 2017 still below the pre-crisis level (Spain, Greece, Italy). In Northern and Western Europe, the impact was more severe for better-off households, or at least more evenly distributed across households.

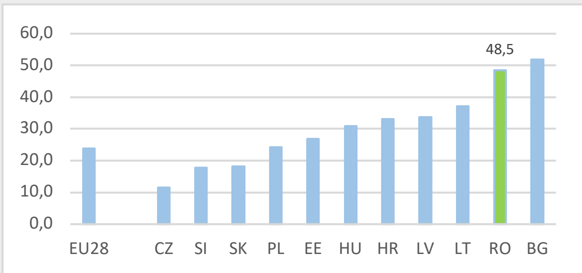
Almost half of people living in rural areas in Romania are at risk of poverty or social exclusion while for urban areas the share is less than 20%. Romania is characterised by strong spatial discrepancies between metropolitan and rural areas, metropolitan areas being specialised in industry and services while rural areas are still heavily based on subsistence agriculture. A large part of farm output is targeted to survival, with insignificant surplus trade. Over the last decade, the share of people at risk of poverty or social exclusion has dropped considerably, however, the reduction across rural areas is less pronounced. A main factor that hinders the development of rural areas is the lack of opportunities and access to well-paid jobs for citizens. Rural population are also generally less educated, which further impedes its development (Precupețu, 2013). In rural areas, schools have weaker infrastructure, less qualified staff, providing thus less opportunities to young people.

Graph 12: People at risk of poverty or social exclusion by degree of urbanisation, 2018



Source: Eurostat, code ilc_peps13

Graph 13: People at risk of poverty or social exclusion in rural areas, 2017



Source: Eurostat, code ilc_peps13

The current economic situation faces several risks with potential negative impact on income distribution: (i) the general government deficit is likely to exceed 3% of GDP which will trigger the Excessive Deficit Procedure and the necessity to adopt correction actions. Possible fiscal adjustment may include: freezing public wages, postponing the pensions increase given the budget impact[8], cutting government expenditure, increasing taxes or introducing new ones, etc., (ii) slowdown in main trading partners, in particular Germany, Italy

[8] A new Pension Law was adopted by the Parliament and provides a gradually increase of the pension point (benchmark used for pension calculation) from September 2019 until September 2021: (i) to RON 1,265 (EUR 268) since September 2019, (ii) to RON 1,775 (EUR 376) as of September 2020, (iii) to RON 1,875 (EUR 397) as of September 2021.

and France, could affect exports, (iii) political uncertainty may postpone domestic and foreign investment.

2. **Policy implications:**

Fiscal policy is the primary tool for government to reshape the income distribution. Fiscal policy redistribution represents a channel that hasn`t been used enough to tackle income inequality and poverty rate. Fiscal redistribution can help raise the income share of the poor and middle class, and thus support inclusive growth. An essential question is how fiscal policy can help achieve redistributive objectives in an efficient manner that is consistent with fiscal sustainability. Evaluating the redistributive impact of fiscal policies requires a comparison of incomes after taxes and transfers with those that would exist in the counterfactual situation. Economic policies addressing specific issues should also be designed having in mind the aim of reducing poverty and income inequality.

Monetary policy seems to have ambiguous distributional effects. The extremely accommodative monetary policy implemented in the aftermath of the financial crisis has had mixed distributional consequences. On one side, there are channels through which monetary policy might have had negative distributional consequences: (i) by boosting assets prices since top-income households hold a larger share or (ii) by increasing the inflation rate which affects in particular the financially-constrained households since they hold more liquid assets. On the other side, monetary policy might have reduced income inequality since borrowers are better-off in a low interest rate environment. In addition, loosening monetary policy boosts demand and job creation, which at the end of the day reduces unemployment, improving the conditions of less skilled workers in particular.

Minimum wage hikes might have played a role in reducing social disparities. The minimum wage is binding in Romania, affecting a large share of workers, more than one third of total employees being paid at the minimum wage level. Despite being raised several times over the last years, the statutory minimum wage in Romania is still one of the lowest among Central and Eastern European countries. Using the minimum wage as a tool to reduce income inequality and in-work poverty has raised concerns, in particular due to a lack of a clear, concrete, and transparent setting mechanism.

Other public policies have a distributional impact. Romania`s expenditure in education and health (as percentage of GDP) is one of the lowest among EU Member States and cannot offer quality services to all its citizens. Public investment in education and health system faces critical challenges, such as low funding and inefficient use of public resources. Furthermore, pronounced brain drain phenomena has resulted in a sizeable shortage of doctors and nurses, despite recent Government′s efforts to considerably increase medical staff`s wages. Public, but also private investment in education and health systems will boost the labour productivity and long-term growth, by moving to higher value-added activities (European Commission, 2019). Likewise, poorly targeted social spending and financial services are important obstacles to reduce inequality and poverty (IMF, 2018).

3. Policy recommendations

Since the adhesion to the European Union, Romania has achieved remarkable progress in reducing poverty rate, but the situation remains delicate and there is still ample room for further improvement. The Government should focus further on:

a) **Improving access to educational and health system for worse-off households.** The Government should implement policies to widen access to high quality early education since the size of early school leavers and NEETs[9] is still large in Romania, affecting in particular young people in rural areas.

b) **Developing *basic financial literacy for adults'* programs.** Public authorities, but also universities should offer free trainings of financial literacy for adults, to help citizens to identify the issues their money management behaviours are triggering. A better understanding of basic financial rules might avoid stressful situations for households, such as those associated with foreign-currency lending (e.g. Swiss franc-denominated loans in the case of Romania)[10].

c) **Improving the access to credit.** In general, poorer households do not have easy access to bank loans and credit constraints lead to an extension of poverty trap. Furthermore, it seems to be a positive correlation between credit availability and upward social mobility. Unequal access to finance can hinder low-income people from investment in human capital and entrepreneurship initiatives.

d) **Setting clear targets to reduce income inequality and poverty rate**. Topmost, adequately designed redistribution via taxes and transfers can be a powerful instrument to reduce income inequality and poverty rate. Given the sensitivity of social issues in

[9] NEETs= not in education, employment or training.

[10] CHF-denominated loans significantly affected borrowers′ repayment capacity. Although in Romania the CHF-denominated loans hold a smaller share than in peer countries, a distinct feature was that they were almost entirely extended to households.

Romania, when promoting new measures, policy makers should consider the distributional impact as well, so ex-ante analysis should be prepared for each draft law.

e) **Improving the quality of institutions**. Countries with weak institutions tend to be more unequal and register a higher level of poverty. In addition, extractive institutions tend to weaken the efficiency of public policies.

f) **Establishing a transparent mechanism for minimum wage setting**. Before any political decision on the minimum wage is taken, the Government should organize real consultation with social partners based on ex-ante assessment. A transparent setting mechanism would also create the basis for a predictable minimum wage policy.

g) **Implementing well-designed structural reforms**, keeping in mind also their distributional effects. Since the main goal of structural reforms is to allow market forces to play a more significant role in the economy, this may induce greater inequality insofar as those households best able to take advantage of market incentives are those with better initial conditions. In a nutshell, structural reforms produce winners and losers. Therefore, when designing structural reforms, policymakers should have in mind the growth – equity trade-offs. Certain structural reforms could further exacerbate income inequality which in turn can make growth more fragile.

h) **Collecting more qualitative data through surveys.** More qualitative data is needed in order to have a complete picture of the current situation. Surveys should be well-designed, well-calibrated, clear, intuitive, and well-targeted. Surveys can be done online at a very large scale in order to receive quick responses. Policy makers should compare survey data with administrative data, as surveys tend to underestimate the number of poor people, but also and rich people and their income (Milanovic, 2016).

4. Concluding remarks

In recent years, Romania has registered one of the highest growth rates among EU Members States. Despite strong growth, some parts of the population have benefitted more than others from the favourable economic situation, raising the perception that some people and places (regions) have been left behind.

Although Romania has made significant progress in reducing the poverty rate, a systematic and structured approach is missing and there is still ample room for improvement. The Government should intensify its poverty reduction efforts by focusing to: improve the access to education and health system for poor households and people in the rural areas in particular, offer financial literacy programs, improve the access to credit, set clear targets to reduce income inequality and poverty rate, improve the quality of institutions, establish a transparent mechanism for minimum wage setting, implement well-designed structural reforms, collecting more qualitative data through surveys.

Given the sensitivity of social issues in Romania, when addressing specific problems, policymakers should have in mind the aim of reducing income inequality and poverty rate. Thus, it is of first order importance to better understand the drivers, transmission channels and consequences of high inequality and poverty rate. Conducting more studies would help policymakers to prioritise actions and improve social aspects.

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Modeling and forecasting the EUR/RON & USD/RON exchange rates volatility using GARCH family models

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Abstract:

This research paper endeavors to study GARCH family models with their modifications, in apprehending the volatility of the EUR/RON & USD/RON exchange rates. Policy makers need detailed forecasts about eventual values of exchange rates. As a result of the fact that exchange rate volatility is an appropriate measure of uneasiness about the economic status of a country. The paper covers both ARCH and GARCH models in order to seize the symmetry effect over the periods from 2005 to 2018. Moreover, the paper applies exponential GARCH (EGARCH) and GJR-GARCH models to apprehend the asymmetry in volatility clustering and the leverage effect in exchange rates. All models were implemented due to the fact that the conditional variance is time-varying and were estimated applying the maximum likelihood estimation (MLE). In addition, by looking at the lowest information criteria (minimum Akaike Information Criterion, minimum Schwarz's Bayesian Information Criterion, minimum Hannan-Quinn Information Criterion) it was possible to find an appropriate GARCH model.

Keywords: ARCH, GARCH, EGARCH, GJR-GARCH, heteroscedasticity, volatility, exchange rate, stationarity, Engle's ARCH test, conditional variances

Number of pages: 23

1. Introduction

In the last decade modeling and forecasting the exchange rate volatility gained a vast theoretical and empirical examination by academics and practitioners alike. There are a number of reasons for this line of analysis. Arguably, understanding the behavior of exchange rate and illustrating the origin of its movements and fluctuations are ones of the most vital concepts in finance.

Volatility is defined as the spread of all potential outcomes of an uncertain variable. Also, volatility in statistics is measured by the standard deviation (variance of returns) and it is usually applied as a measure of risk.

After the collapse of the Bretton Woods agreement in March 1973 when numerous countries shifted from fixed exchange rate regime towards floating exchange rate, followed by the US dollar depreciation in February 1973, the issue of modeling and forecasting the exchange rate movements and fluctuations became a major topic of macroeconomic analysis.

Researchers like McKenzie and Faff (2004), Engel and Kenneth (2005), Andersen and Bollerslev (1998) and Hartman (1972) pointed that between news on macroeconomic fundgaments such as interest rates, GDP, inflation, money supply and exchange rate volatility exists a somewhat connection. Furthermore, in the recent years, several studies have been elaborated in empirical finance to study the characteristics of exchange rate volatility. It was established by researchers such as Hsieh (1988, 1989), Black (1976), Mandelbrot (1963), Bollerslev (1987,1980), Friedman and Vandersteel (1982), Brooks and Burke (1998) that the stylized characteristics of the returns exhibit a leptokurtic distribution instead of a normal one, a non-linear time dependence and fatter tails. Moreover, according to their papers, they found an evidence of volatility clustering and persistence, and also deducted the existence of asymmetric effects in returns.

The model developed by Engle (1982), ARCH, and elaborated independently by Bollerslev (1986) and Taylor (1986), GARCH, is often implemented in measuring the uncertainty/ volatility of exchange rates.

2. Literature review

Both ARCH and GARCH processes can be utilized in capturing the volatility clustering and leptokurtosis, but they cannot model the leverage effect. Thus, the GARCH model, elaborated by Bollerslev and Taylor, allows a more flexible lag structure and significantly reduces the number of estimated parameters.

In order to overcome this limitation, researchers made numerous modifcations of the GARCH process that led to the Exponential GARCH (EGARCH) model by Nelson (1991), the Treshold GARCH (TGARCH/ZGARCH) of Zakoian (1994) and the GJR-GARCH model by Glosten et al (1993). Moreover, Bollerslev (1987), Baillie and Bollerslev (1989), Beine et al (2002) discovered that the GARCH models have another limitation in not being capable to entirely capture the leptokurtic characteristic of high frequency time series data. Also, to address this problem, it was used the Student's-t distribution in order to model the innovation (shocks) of the variance equation.

3. Econometric methodology

3.1. Stylized facts

- Fat tails (leptokurtosis)= It was observed that when we are comparing the financial time series distribution with the normal distribution, fatter tails are present (also known as excess Kurtosis).
- Volatility clustering and persistence (volatility pooling) = Volatility in financial markets tend to appear in clusters. Thus, large values are presumed to follow large changes and small values seem to follow small changes. A plausible explanation seems to be that volatility pooling is an accumulation of information.
- Leverage effects= It appears that volatility tends to rise more after negative shocks than after positive ones of similar magnitude.

- Long memory= For high frequency data, volatility is heavily persistent and it can be observed that exists proof of near unit root demeanor in the conditional variance process.
- Co-movements in volatility= It appears that when we are looking at financial time series in different markets, big movements in a particular currency are being followed by big movements in another on FX market.

3.2. Autoregressive Integrated Moving Average (ARIMA) model

Before analyzing the conditional variance model, we need to estimate the adequate conditional mean model. The Box-Jenkins (1976) methodology is an approach on time series analysis in order to discover an ARMA (p, q) model which provides a parsimonious explanation of a stationary stochastic process. This methodology includes four stages, identification, estimation, diagnostic checking and forecasting. Furthermore, in the first scenario, data needs to be transformed to have a stationary series.

The AR(I)MA (p, d, q) model can be expressed as:

$$\varphi_p(L)(1-L)^d(y_t-\mu)=\omega_q(L)e_t,$$

Where:

y_t is the time series;

L is the difference operator: $\Delta y_t = y_t - y_{t-1} = (1-L)y_t$;

d is the order of the difference operator;

e_t is the random error at the time t;

μ is the mean of the model;

$\varphi_p(L) = 1 - \sum_{i=1}^{p} \varphi_i L^i$ and $\omega_q = 1 - \sum_{j=1}^{q} \omega_j L^j$ are polynomials in terms of L;

φ_p , ω_q are the parameters of autoregressive (AR) and moving average (MA) terms with p and q orders.

3.3. ARCH model

The fundamental ARCH model suggested by Engle (1982) is defined as:

$$\varepsilon_t = v_t\sqrt{\alpha_0 + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2} \ ,$$

where $\alpha_0 \geq 0$, $1 \geq \alpha_i \geq 0$ and v_t is independent identically distributed process with the mean equal to zero and the variance equal to 1.

The ARCH model issue is the fact that it assumes the positive and the negative shocks have similar or the same impact on volatility because it relies on the square of prior shocks. This may not occur in practice.

3.4. GARCH model

So, in 1986 Bollerslev and Taylor extended the basic ARCH model into a model that allows the conditional variance to rely on its own lags. Furthermore, it reduces the number of the estimated parameters from infinitely to just a few.

$$\varepsilon_t = v_t\sqrt{h_t},$$

where $h_t = \alpha_0 + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \sum_{i=i}^{p} \beta_i \, h_{t-i}$, v_t is i.i.d, $\alpha_0, \alpha_i, \beta_i$ are parameters to estimate (all parameters must be positive and we expect that the value of the α_0 to be small).

Parameter α_i analysis the response of uncertainty on market variances and β_i displays the difference which was resulted from outliers on conditional variance. We also expect the relationship $\alpha_i + \beta_i$<1 to be true.

3.5. EGARCH model

The ARCH, respectively GARCH models focus primarily on the size of conditional variance on returns and ignore details about the positive or the negative direction. The Exponential GARCH (EGARCH) model, developed by Nelson (1991), is considered as a model that catches the asymmetric reactions of varying variance to innovation (shocks).

$\varepsilon_t = z_t\sigma_t$, where z_t is white noise

$$\log(\sigma_t^2) = \omega + \sum_{i=1}^{p} \alpha_i \left|\frac{\varepsilon_{t-i}}{\sigma_{t-i}}\right| + \sum_{j=1}^{q} \beta_j \log(\sigma_{t-j}^2) + \sum_{k=1}^{r} \gamma_k \frac{\varepsilon_{t-k}}{\sigma_{t-k}}$$

σ_t^2 is the conditional variance, $\alpha_i, \beta_j, \omega$ and γ_k are parameters to be estimated where γ_k, α_i and ω have no restrictions. Also, γ_k is an indicator of leverage effect (meaning that it must be statistically significant and negative)

Compared to the normal GARCH, we can observe that the EGARCH has many advantages such as:

- The EGARCH model can efficaciously define the modifications of volatility.
- The logarithmic form enables the positive constraint of the parameters.
- The EGARCH model includes asymmetries in the modifications of the volatility of returns.

3.6. GJR-GARCH model

The GJR-GARCH (p, q) model, developed by Glosten, Jagannatahan and Runkle, is other asymmetric GARCH model suggested.

$$\sigma_t^\delta = \omega + \sum_{i=1}^{p} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{q} \beta_j \sigma_{t-j}^2 + \gamma_i I_{t-i} \varepsilon_{t-i}^2,$$

where $\omega, \alpha_i, \beta_j$ and γ_i are parameters to estimate. Also, we assume that the parameters are positive in order to the relationship $\alpha_i + \beta_j + \frac{\gamma_i}{2} < 1$ to be valid.

$$I_{t-i} = \begin{cases} 1 \; when \; \varepsilon_{t-i} < 0 \\ 0 \; when \; \varepsilon_{t-i} \geq 0 \end{cases},$$

where I_{t-i} is a dummy variable. If $\gamma_i > 0$, the negative shocks (bad news) have a grater impact than positive shocks.

3.7. Conditional Distributions

- Normal distribution:

$$\ln L[(y_t), \theta] = -\frac{1}{2}[\, T\ln(2\pi) + \sum_{t=1}^{T} z_t^2 + \sum_{t=1}^{T} \ln(\sigma_t^2)],$$

where T represents the observations and θ is the vector of the parameters. Moreover, the vector must be estimated for the conditional mean, density function and conditional variance.

- Student-t Distribution:

The Student-t distribution can manipulate more severe leptokurtosis and is symmetric around 0.

$$\ln L[(y_t), \theta] = T[\ln\Gamma\left(\frac{\upsilon+1}{2}\right) - \ln\Gamma\left(\frac{\upsilon}{2}\right) - \frac{1}{2}\ln[\pi(\upsilon-2)] - \frac{1}{2}\sum_{t=1}^{T}[\ln(\sigma_t^2) + (1+\upsilon)\ln(1+\frac{z_t^2}{v-2})],$$

where $\Gamma(\upsilon) = \int_0^\infty e^{-x} x^{\upsilon-1} dx$ represents the Gamma function and υ reflects the degree of freedom. The Normal distribution is included in the Student-t distribution as a special event when $\upsilon = \infty$.

4. Data Source

The intent of this paper is to compute two asymmetric GARCH models (EGARCH, GJR-GARCH) using EUR/RON and USD/RON exchange rates data, collected from the National Bank of Romania, for the period 04-July-2005 to 18-October-2019, representing 3620 daily observations. Starting from the fundamental concept of return series. So, in comparison with exchange rates, returns have more suited econometric properties. Meaning that it is much easy to handle the returns than the prices (exchange rates).

Let Z_k be the daily log return series.

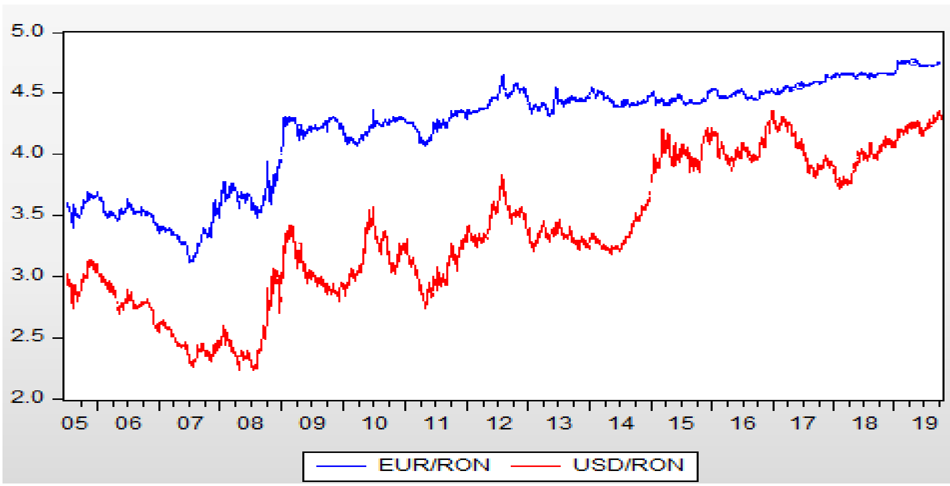
$$Z_k = \log\left(\frac{P_k}{P_{k-1}}\right) = \log(P_k) - \log(P_{k-1}),$$

where P_k represents the exchange rate at time k.

5. Empirical results

The daily EUR/USD and USD/RON exchange rates are illustrated in Figure 1 and Figure 2. Also, at first glance, we can observe that are significant ups and downs in the exchange rate, meaning that it is possible to conclude that the data is not stationary.

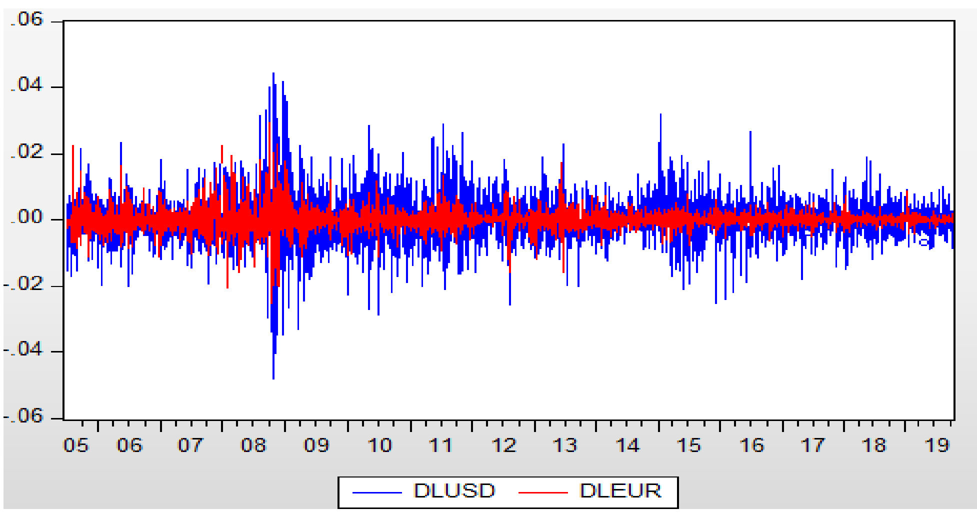
Figure 1: Currencies exchange rate



Source: Author's computations

From Figure 2 we can observe that without being affected by stationarity anymore, the exchange rate returns seem to show uncertainty.

Figure 2: Exchange rate returns



Source: Author's computations

To specify the distributional characteristics of the returns, several descriptive statistics were estimated on the data set. The summary statistics for the exchange rates, along with the Jarque-Bera test are presented in Table 1. Furthermore, the Jarque-Bera test represents a goodness-of-fit test. The JB test is defined as:

$$JB = \frac{n}{6}\left(s^2 + \frac{(k-3)^2}{4}\right),$$

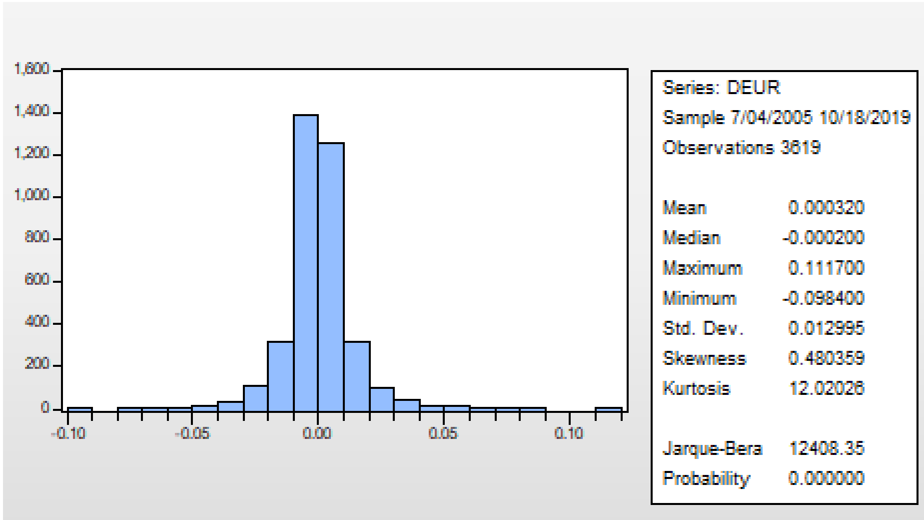
where *n* illustrates the sample size, *s* represents the Skewness and *k* is the Kurtosis. Also, the JB null hypothesis is that the data follows a normal distribution.

$S = \frac{1}{T}\sum_{t=1}^{T}(\frac{x_{t-}\bar{x}}{\hat{\sigma}})^3$, represents the Skewness, where the third moment illustrates the asymmetry.

$K = \frac{1}{T}\sum_{t=1}^{T}(\frac{x_t-\bar{x}}{\hat{\sigma}})^4$, illustrates the Kurtosis, where the fourth moment displays a measure of the peakness.

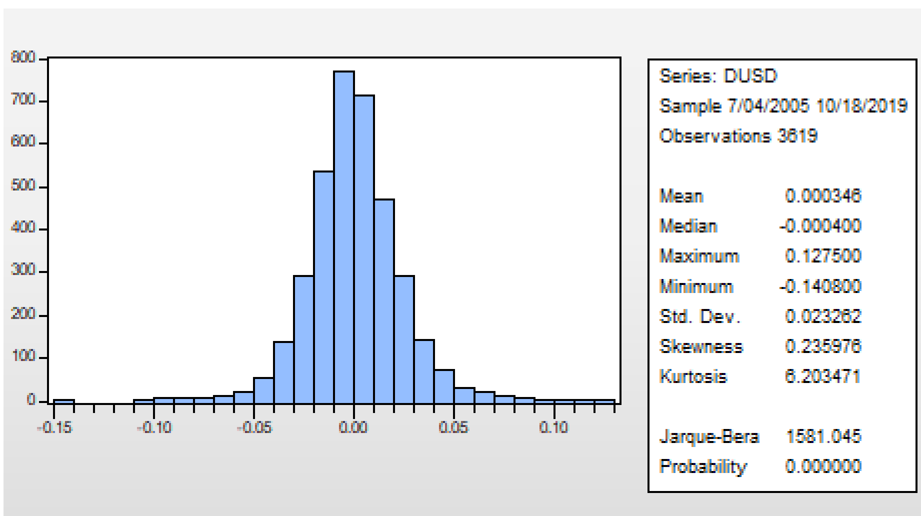
According with the results from Table 1, where P-value < 5% (significance level), both USD_RON and EUR_RON daily returns do not follow the normal distribution. Moreover, asymmetry's coefficient illustrates that the distribution of the returns is right asymmetric in both cases and also has fatter tails than the normal distribution respectively. Also, this means that especially high and low realizations take place more frequently than under the normality distribution hypothesis.

Figure 3: Normality test EUR_USD



Source: Author's computations

Figure 4: Normality test USD_RON



Source: Author's computations

For high frequency data, uncertainty is heavily persistent (Long memory) and it is a strong evidence of unit root behavior of the conditional variance (Longmore and Robinson, 2004). The Augmented Dickey-Fuller (ADF), Kwiatkowski–Phillips–Schmidt–Shin (KPSS) and Phillip-Perron (PP) methods are elaborated in order to check the existence of a unit root.

Table 1: Unit Root tests

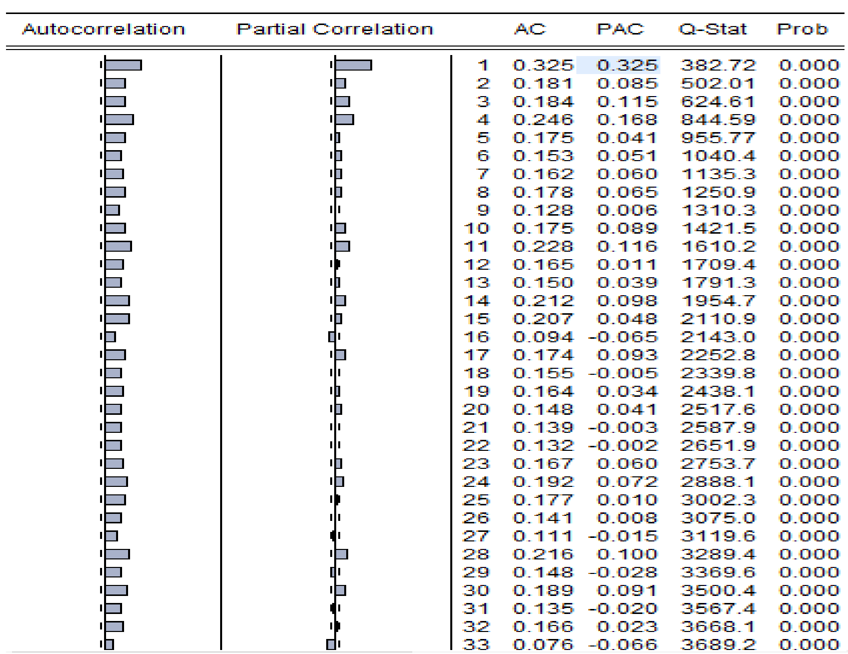
Variable	ADF		KPSS		PP	
	P-value	**Null Rejected**	**P-value**	**Null Rejected**	**P-value**	**Null Rejected**
USD_RON	0	TRUE	0.1000	FALSE	0	TRUE
EUR_RON	0	TRUE	0.1000	FALSE	0	TRUE

Source: Author's computations

According to the results in Table 2, the daily exchange rate returns of both USD_RON and EUR_RON are stationary in their levels in all tests.

So, the problem of the stationarity does not exist anymore. Furthermore, after identifying the stationarity, we need to find the proper ARMA (p,q) model .

Figure 4: EUR_RON ACF and PACF



Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.325	0.325	382.72	0.000
		2	0.181	0.085	502.01	0.000
		3	0.184	0.115	624.61	0.000
		4	0.246	0.168	844.59	0.000
		5	0.175	0.041	955.77	0.000
		6	0.153	0.051	1040.4	0.000
		7	0.162	0.060	1135.3	0.000
		8	0.178	0.065	1250.9	0.000
		9	0.128	0.006	1310.3	0.000
		10	0.175	0.089	1421.5	0.000
		11	0.228	0.116	1610.2	0.000
		12	0.165	0.011	1709.4	0.000
		13	0.150	0.039	1791.3	0.000
		14	0.212	0.098	1954.7	0.000
		15	0.207	0.048	2110.9	0.000
		16	0.094	-0.065	2143.0	0.000
		17	0.174	0.093	2252.8	0.000
		18	0.155	-0.005	2339.8	0.000
		19	0.164	0.034	2438.1	0.000
		20	0.148	0.041	2517.6	0.000
		21	0.139	-0.003	2587.9	0.000
		22	0.132	-0.002	2651.9	0.000
		23	0.167	0.060	2753.7	0.000
		24	0.192	0.072	2888.1	0.000
		25	0.177	0.010	3002.3	0.000
		26	0.141	0.008	3075.0	0.000
		27	0.111	-0.015	3119.6	0.000
		28	0.216	0.100	3289.4	0.000
		29	0.148	-0.028	3369.6	0.000
		30	0.189	0.091	3500.4	0.000
		31	0.135	-0.020	3567.4	0.000
		32	0.166	0.023	3668.1	0.000
		33	0.076	-0.066	3689.2	0.000

Source: Author's computations

Figure 5: USD_RON ACF and PACF

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.255	0.255	235.31	0.000
		2	0.201	0.145	381.13	0.000
		3	0.195	0.125	518.88	0.000
		4	0.173	0.087	626.93	0.000
		5	0.192	0.106	760.32	0.000
		6	0.074	-0.041	780.23	0.000
		7	0.145	0.078	856.58	0.000
		8	0.164	0.081	953.63	0.000
		9	0.170	0.082	1058.9	0.000
		10	0.196	0.097	1198.3	0.000
		11	0.173	0.064	1306.7	0.000
		12	0.187	0.060	1433.7	0.000
		13	0.175	0.050	1545.4	0.000
		14	0.246	0.137	1765.1	0.000
		15	0.188	0.042	1893.9	0.000
		16	0.129	-0.011	1954.5	0.000
		17	0.181	0.059	2073.2	0.000
		18	0.157	0.024	2162.4	0.000
		19	0.207	0.081	2317.9	0.000
		20	0.191	0.069	2450.2	0.000
		21	0.131	-0.016	2513.0	0.000
		22	0.163	0.014	2609.6	0.000
		23	0.123	-0.019	2665.1	0.000
		24	0.199	0.073	2809.2	0.000
		25	0.093	-0.061	2840.5	0.000
		26	0.138	0.029	2909.5	0.000
		27	0.134	-0.011	2974.7	0.000
		28	0.135	0.002	3041.5	0.000
		29	0.134	-0.014	3107.2	0.000
		30	0.098	-0.013	3142.4	0.000
		31	0.158	0.029	3233.2	0.000
		32	0.115	-0.023	3281.2	0.000
		33	0.130	0.006	3343.0	0.000
		34	0.228	0.114	3532.3	0.000

Source: Author's computations

According with the Figure 4, respectively Figure 5, it is demonstrated that the Ljung-Box (1978) statistic for all lags of the square returns of autocorrelation function (ACF) of both series are significant. Also, by looking at the ACF and PACF for both series it has been detected autoccorelation. Furthermore, due to the autoccorelation presented at lags 4 and 5 for both series, we concluded that an ARMA (4,1) is one of the most suited model for EUR_RON data series and for USD_RON it was displayed an ARMA (5,5) model.

After, the identification of ARMA models, we analzyed the presence of conditional heteroscedasticity from squared returns. Moreover, after elaborating the ARCH test on both exchange rates series we discovered that the null hypothesis is rejected due to the fact that P-value is less than significance level.

Consequently, the absence of ARCH effect on both models is rejected.

Figure 6: USD_RON ARCH test

Heteroskedasticity Test: ARCH

F-statistic	251.2706	Prob. F(1,3616)	0.0000
Obs*R-squared	235.0746	Prob. Chi-Square(1)	0.0000

Test Equation:
Dependent Variable: RESID^2
Method: Least Squares
Date: 11/11/19 Time: 18:18
Sample (adjusted): 7/06/2005 10/18/2019
Included observations: 3618 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	3.85E-05	2.21E-06	17.43299	0.0000
RESID^2(-1)	0.254899	0.016080	15.85152	0.0000

R-squared	0.064974	Mean dependent var	5.17E-05
Adjusted R-squared	0.064715	S.D. dependent var	0.000127
S.E. of regression	0.000123	Akaike info criterion	-15.16624
Sum squared resid	5.48E-05	Schwarz criterion	-15.16281
Log likelihood	27437.72	Hannan-Quinn criter.	-15.16502
F-statistic	251.2706	Durbin-Watson stat	2.073947
Prob(F-statistic)	0.000000		

Source: Author's computations

Figure 7: EUR_RON ARCH test

Heteroskedasticity Test: ARCH

F-statistic	427.2497	Prob. F(1,3616)	0.0000
Obs*R-squared	382.3136	Prob. Chi-Square(1)	0.0000

Test Equation:
Dependent Variable: RESID^2
Method: Least Squares
Date: 11/11/19 Time: 18:19
Sample (adjusted): 7/06/2005 10/18/2019
Included observations: 3618 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	7.41E-06	6.29E-07	11.78522	0.0000
RESID^2(-1)	0.325069	0.015727	20.67002	0.0000

R-squared	0.105670	Mean dependent var	1.10E-05
Adjusted R-squared	0.105423	S.D. dependent var	3.84E-05
S.E. of regression	3.64E-05	Akaike info criterion	-17.60606
Sum squared resid	4.78E-06	Schwarz criterion	-17.60264
Log likelihood	31851.37	Hannan-Quinn criter.	-17.60484
F-statistic	427.2497	Durbin-Watson stat	2.055111
Prob(F-statistic)	0.000000		

Source: Author's computations

Since there are ARCH/GARCH effects on the returns of the USD_RON and EUR_RON, we can advance with the estimation of GARCH family models. After elaborated the GARCH, EGARCH and GJR-GARCH models, it is imperative comparing the goodness of fit. One of the basics criterions used in practice and also by researchers are the Akaike Information Criterion, Bayesian Information Criterion and Hannan-Quinn Criterion. The information criterions are defined as:

$$AIC = -2\log(L) + 2k,$$

$$HQ = -2L_{max} + 2kln[\ln(n)],$$

$$BIC = -2\log(L) + klog(n),$$

where L represents the maximized value of the likelihood function, k is the number of free parameters in order to be estimated and n illustrates the number of observations.

Table 2: Model comparison

EUR_RON	ARMA (4,1)-GARCH (1,1)	ARMA (4,1)-EGARCH (1,1)	ARMA (4,1)-GJRGARCH (1,1)	***USD_RON***	ARMA (5,5)-GARCH (1,1)	ARMA (5,5)-EGARCH (1,1)	ARMA (5,5)-GJRGARCH (1,1)
AIC	-9.199665	-9.197745	-9.197290	**AIC**	-7.260452	-7.257903	-7.261863
BIC	-9.189387	-9.187467	-9.185298	***BIC***	-7.250171	-7.247622	-7.249869
HQ	-9.196003	-9.194083	-9.193017	***HQ***	-7.256789	-7.254240	-7.257589

Source: Author's computations

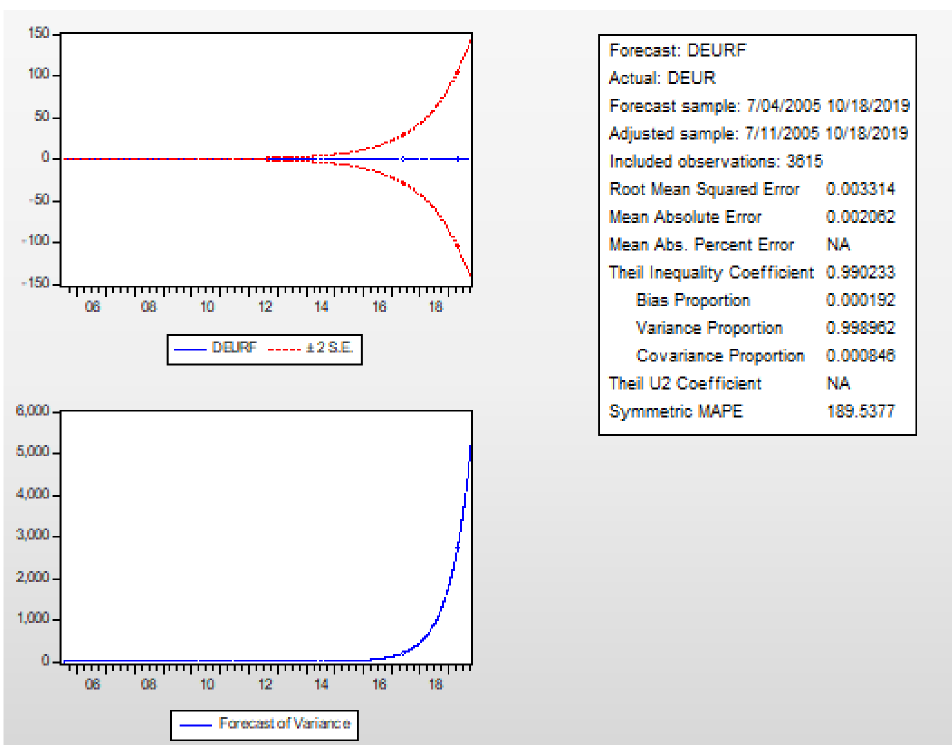
In order to verify the most appropriate GARCH model for the daily returns of EUR_RON, respectively USD_RON, it is regarded to identify the models with the minimum value of information criterions.

According to the Table 2, we can observe the fact that the most suitable GARCH model for both series is the GARCH (1,1)[1]. Also, it was noted that in absolutely all cases the coefficients are statistically significant at a 5% level of confidence. Moreover, the leverage effect is seized from the estimation of GARCH (1,1) model.

6. Forecasting the volatility

Figure 8 and 9 illustrates the Root Mean Squared Error (RMSE), Mean Absolute Error (MAE) and Theil's U-statistic for the forecast volatility of both exchange rates. Particularly, the lower values of RMSE and MAE resulted by performing the GARCH (1,1) model point out that the model has greater forecasting power. Moreover, The Theil's statistic is 0.990233 for EUR_RON, respectively 0.958238 for USD_RON is less than one which illustrates that the forecasts are accurate.

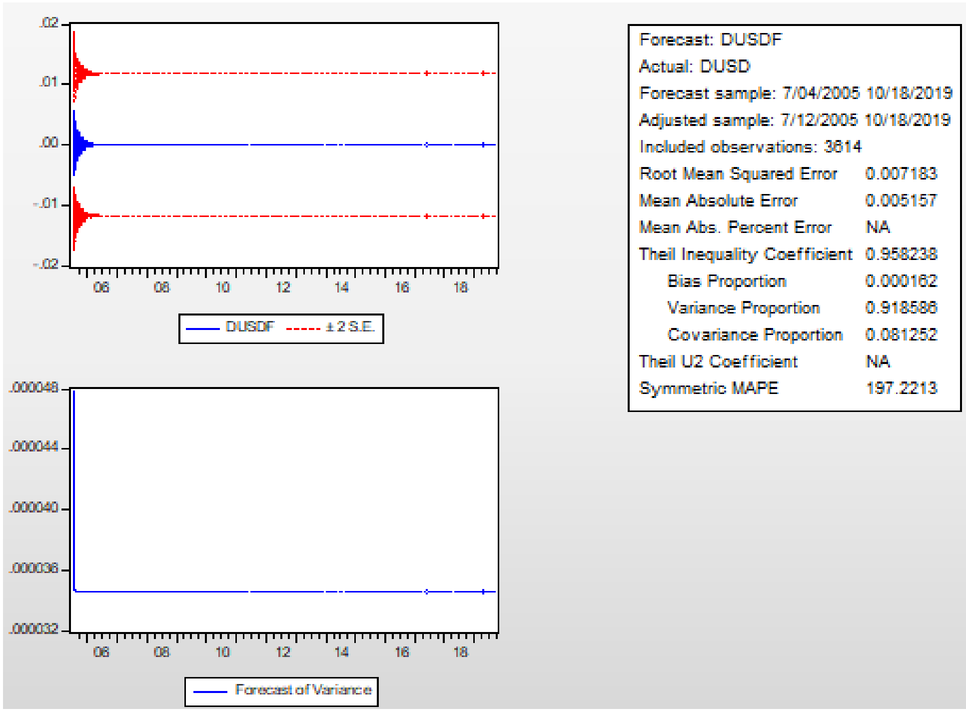
Figure 8: Forecast EUR_RON



Source: Author's computations

[1] As error distribution it was utilized the Gaussian Distribution.

Figure 9: Forecast USD_RON



Source: Author's computations

7. Conclusions

Economic policy makers need to forecast the future values of exchange rate utilizing the equivalent models. In the last period, in the financial world, the relevance of this problem increased due to the fact that the instability of the exchange rates may enhance the transactions costs and reduce the benefits of international trade.

This research paper aims to investigate the volatility properties accompanied with exchange uncertainty. Also, the paper implements the EGARCH and GJR-GARCH models in order to investigate the asymmetry in volatility clustering and the leverage effect. The results, suggested that the EUR_RON and USD_RON exchange rates illustrated the persistence of conditional variance (volatility), meaning that the exchange rate behavior is influenced by previous information. To address this issue, it was implemented the GARCH family models which can adequately model the volatility.

To sum up, the outcomes of this paper confirm prior findings that symmetric GARCH models do not seem to capture the leptokurtosis.

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Appendix

Figure 10: ARMA (4,1)-GARCH (1,1) EUR_RON

Dependent Variable: DEUR
Method: ML ARCH - Normal distribution (BFGS / Marquardt steps)
Date: 11/11/19 Time: 18:23
Sample (adjusted): 7/11/2005 10/18/2019
Included observations: 3615 after adjustments
Convergence achieved after 30 iterations
Coefficient covariance computed using outer product of gradients
MA Backcast: 7/08/2005
Presample variance: backcast (parameter = 0.7)
GARCH = C(4) + C(5)*RESID(-1)^2 + C(6)*GARCH(-1)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	3.20E-05	2.97E-05	1.077242	0.2814
AR(4)	-0.037105	0.017302	-2.144485	0.0320
MA(1)	0.077118	0.016883	4.567901	0.0000
		Variance Equation		
C	8.26E-08	7.11E-09	11.62521	0.0000
RESID(-1)^2	0.147153	0.007817	18.82546	0.0000
GARCH(-1)	0.858251	0.006292	136.3957	0.0000

R-squared	0.022599	Mean dependent var	7.80E-05
Adjusted R-squared	0.022058	S.D. dependent var	0.003314
S.E. of regression	0.003278	Akaike info criterion	-9.199665
Sum squared resid	0.038805	Schwarz criterion	-9.189387
Log likelihood	16634.39	Hannan-Quinn criter.	-9.196003
Durbin-Watson stat	1.811091		

Source: Author's computations

Figure 11: ARMA (4,1)-EGARCH (1,1)

Dependent Variable: DEUR
Method: ML ARCH - Normal distribution (BFGS / Marquardt steps)
Date: 11/11/19 Time: 18:25
Sample (adjusted): 7/11/2005 10/18/2019
Included observations: 3615 after adjustments
Convergence achieved after 46 iterations
Coefficient covariance computed using outer product of gradients
MA Backcast: 7/08/2005
Presample variance: backcast (parameter = 0.7)
LOG(GARCH) = C(4) + C(5)*ABS(RESID(-1)/@SQRT(GARCH(-1))) + C(6)
*LOG(GARCH(-1))

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	3.02E-05	2.32E-05	1.301055	0.1932
AR(4)	-0.037279	0.016173	-2.304962	0.0212
MA(1)	0.079769	0.016144	4.940997	0.0000
		Variance Equation		
C(4)	-0.565034	0.033123	-17.05846	0.0000
C(5)	0.303432	0.012353	24.56400	0.0000
C(6)	0.971234	0.002185	444.5719	0.0000

R-squared	0.023086	Mean dependent var	7.80E-05
Adjusted R-squared	0.022545	S.D. dependent var	0.003314
S.E. of regression	0.003277	Akaike info criterion	-9.197745
Sum squared resid	0.038786	Schwarz criterion	-9.187467
Log likelihood	16630.92	Hannan-Quinn criter.	-9.194083
Durbin-Watson stat	1.816069		

Source: Author's computations

Figure 12: ARMA (4,1)-GJRGARCH (1,1)

Dependent Variable: DEUR
Method: ML ARCH - Normal distribution (BFGS / Marquardt steps)
Date: 11/11/19 Time: 18:27
Sample (adjusted): 7/11/2005 10/18/2019
Included observations: 3615 after adjustments
Convergence achieved after 59 iterations
Coefficient covariance computed using outer product of gradients
MA Backcast: 7/08/2005
Presample variance: backcast (parameter = 0.7)
LOG(GARCH) = C(4) + C(5)*ABS(RESID(-1)/@SQRT(GARCH(-1))) + C(6)
*RESID(-1)/@SQRT(GARCH(-1)) + C(7)*LOG(GARCH(-1))

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	2.95E-05	2.46E-05	1.198989	0.2305
AR(4)	-0.032761	0.016218	-2.019956	0.0434
MA(1)	0.079022	0.016193	4.879908	0.0000
Variance Equation				
C(4)	-0.570150	0.033524	-17.00703	0.0000
C(5)	0.304382	0.012441	24.46550	0.0000
C(6)	0.006068	0.006881	0.881891	0.3778
C(7)	0.970867	0.002214	438.4605	0.0000

R-squared	0.022798	Mean dependent var	7.80E-05
Adjusted R-squared	0.022257	S.D. dependent var	0.003314
S.E. of regression	0.003277	Akaike info criterion	-9.197290
Sum squared resid	0.038797	Schwarz criterion	-9.185298
Log likelihood	16631.10	Hannan-Quinn criter.	-9.193017
Durbin-Watson stat	1.814142		

Source: Author's computations

Figure 13: ARMA (5,5)-GARCH (1,1)

Dependent Variable: DUSD
Method: ML ARCH - Normal distribution (BFGS / Marquardt steps)
Date: 11/11/19 Time: 18:32
Sample (adjusted): 7/12/2005 10/18/2019
Included observations: 3614 after adjustments
Convergence achieved after 67 iterations
Coefficient covariance computed using outer product of gradients
MA Backcast: 7/05/2005 7/11/2005
Presample variance: backcast (parameter = 0.7)
GARCH = C(4) + C(5)*RESID(-1)^2 + C(6)*GARCH(-1)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	3.04E-05	9.64E-05	0.315307	0.7525
AR(5)	-0.920266	0.044091	-20.87221	0.0000
MA(5)	0.919075	0.044752	20.53687	0.0000
Variance Equation				
C	2.18E-07	5.62E-08	3.884473	0.0001
RESID(-1)^2	0.038450	0.003558	10.80522	0.0000
GARCH(-1)	0.957012	0.003932	243.4111	0.0000

R-squared	0.001869	Mean dependent var	9.97E-05
Adjusted R-squared	0.001316	S.D. dependent var	0.007191
S.E. of regression	0.007186	Akaike info criterion	-7.260452
Sum squared resid	0.186467	Schwarz criterion	-7.250171
Log likelihood	13125.64	Hannan-Quinn criter.	-7.256789
Durbin-Watson stat	1.929785		

Inverted AR Roots	.80-.58i -.98	.80+.58i	-.30+.94i	-.30-.94i
Inverted MA Roots	.80-.58i -.98	.80+.58i	-.30+.94i	-.30-.94i

Source: Author's computations

Figure 14: ARMA (5,5)-EGARCH (1,1)

Dependent Variable: DUSD
Method: ML ARCH - Normal distribution (BFGS / Marquardt steps)
Date: 11/11/19 Time: 18:34
Sample (adjusted): 7/12/2005 10/18/2019
Included observations: 3614 after adjustments
Convergence achieved after 53 iterations
Coefficient covariance computed using outer product of gradients
MA Backcast: 7/05/2005 7/11/2005
Presample variance: backcast (parameter = 0.7)
LOG(GARCH) = C(4) + C(5)*ABS(RESID(-1)/@SQRT(GARCH(-1))) + C(6)
*LOG(GARCH(-1))

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	7.02E-05	9.44E-05	0.744152	0.4568
AR(5)	-0.489860	0.191529	-2.557631	0.0105
MA(5)	0.501632	0.189234	2.650861	0.0080
Variance Equation				
C(4)	-0.152111	0.020351	-7.474502	0.0000
C(5)	0.101052	0.008361	12.08581	0.0000
C(6)	0.992594	0.001660	597.7686	0.0000

R-squared	0.001656	Mean dependent var	9.97E-05
Adjusted R-squared	0.001103	S.D. dependent var	0.007191
S.E. of regression	0.007187	Akaike info criterion	-7.257903
Sum squared resid	0.186507	Schwarz criterion	-7.247622
Log likelihood	13121.03	Hannan-Quinn criter.	-7.254240
Durbin-Watson stat	1.927303		

Source: Author's computations

Figure 15: ARMA (5,5)-GJRGARCH (1,1)

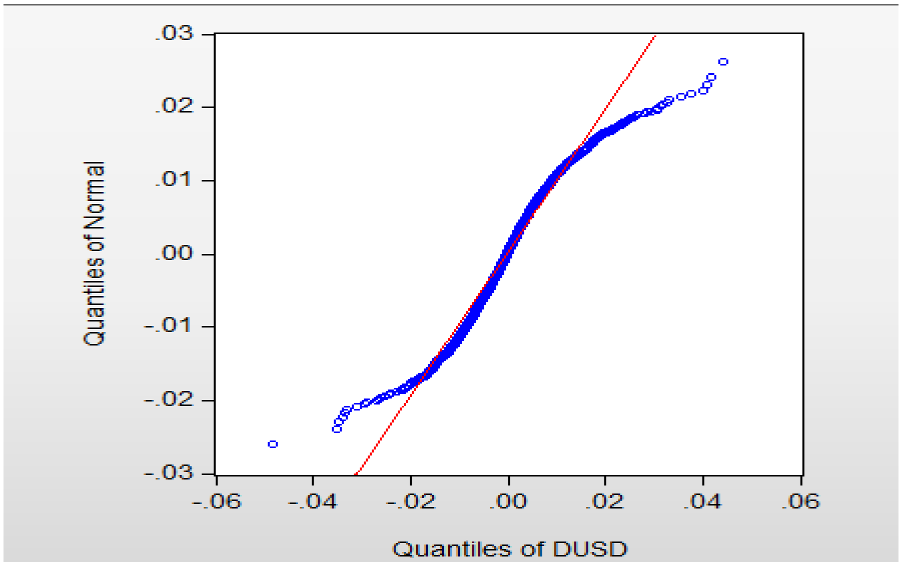
Dependent Variable: DUSD
Method: ML ARCH - Normal distribution (BFGS / Marquardt steps)
Date: 11/11/19 Time: 18:35
Sample (adjusted): 7/12/2005 10/18/2019
Included observations: 3614 after adjustments
Failure to improve likelihood (singular hessian) after 57 iterations
Coefficient covariance computed using outer product of gradients
MA Backcast: 7/05/2005 7/11/2005
Presample variance: backcast (parameter = 0.7)
LOG(GARCH) = C(4) + C(5)*ABS(RESID(-1)/@SQRT(GARCH(-1))) + C(6)
*RESID(-1)/@SQRT(GARCH(-1)) + C(7)*LOG(GARCH(-1))

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.000116	9.60E-05	1.205811	0.2279
AR(5)	-0.920617	0.043133	-21.34356	0.0000
MA(5)	0.920774	0.043342	21.24417	0.0000
Variance Equation				
C(4)	-0.140725	0.018996	-7.408177	0.0000
C(5)	0.091406	0.008274	11.04774	0.0000
C(6)	0.021408	0.004362	4.907699	0.0000
C(7)	0.992999	0.001550	640.7676	0.0000

R-squared	0.002110	Mean dependent var	9.97E-05
Adjusted R-squared	0.001557	S.D. dependent var	0.007191
S.E. of regression	0.007185	Akaike info criterion	-7.261863
Sum squared resid	0.186422	Schwarz criterion	-7.249869
Log likelihood	13129.19	Hannan-Quinn criter.	-7.257589
Durbin-Watson stat	1.929927		

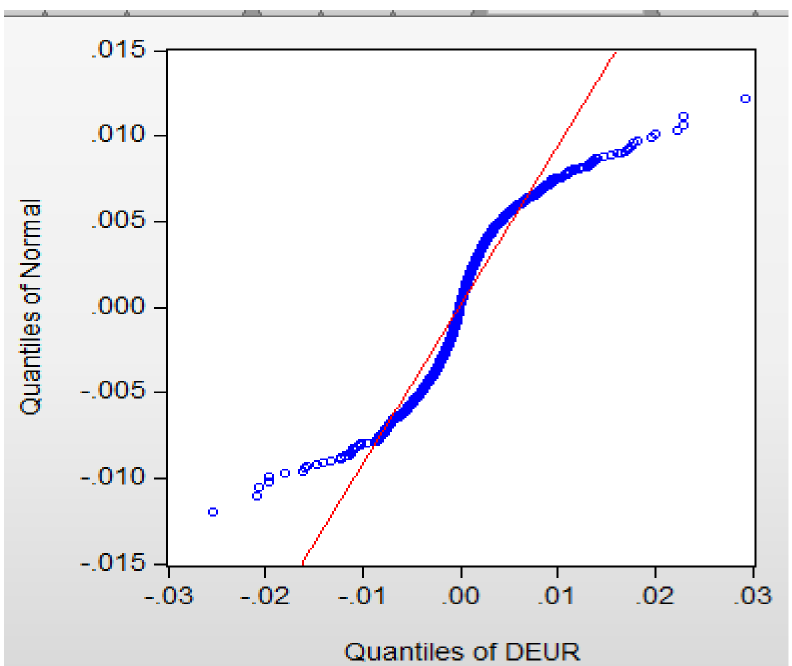
Source: Author's computations

Figure 16: QQ plot USD_RON



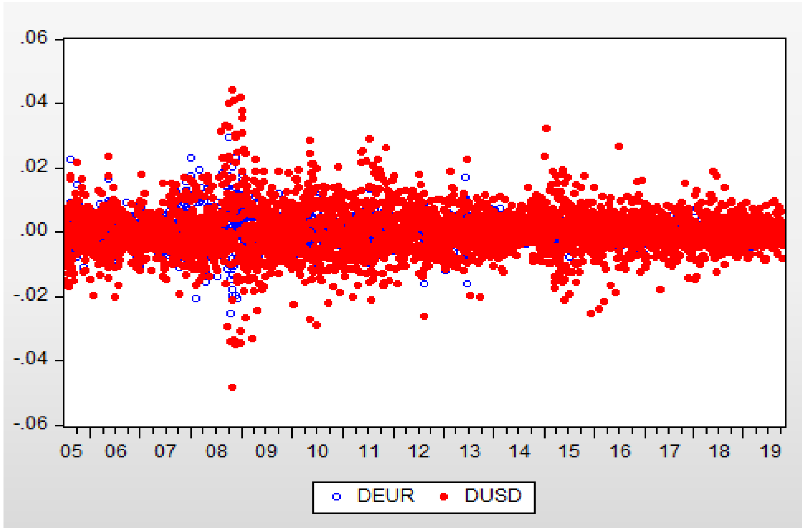
Source: Author's computations

Figure 17: QQ plot EUR_RON



Source: Author's computations

Figure 18: EUR_RON and USD_RON plot



Source: Author's computations