DOES FINANCIAL DEVELOPMENT LIFT UP THE "SMALL BOATS"?

A Comparative Analysis on the Financial Development – Income Inequality Nexus[§]

Mihaela – Claudia POP[‡]

Summary

In line with Zhang and Naceur (2019), this paper follows a multidimensional approach, shedding new light on the existent literature by looking at whether and how different dimensions of financial development determine income inequality across countries. We investigate eight indicators that portray the depth, efficiency and stability of financial institutions and financial markets, as well as the access to these ones. We contribute to the literature by assessing how these financial development dimensions are associated with both gross and net income inequality. Conversely, most of the studies focus only on the pre-taxes income inequality as it does not interfere with the redistribution policies via taxation (deHaan and Sturm, 2017). Our choice of the Gini coefficient has been documented with favourable arguments for using the new Standardized World Income Inequality Database (SWIID) developed by Solt (2019), to the detriment of other sources extensively-used in the literature. To our knowledge, SWIID is the most comprehensive and standardized income inequality database (Ortiz and Cummins, 2011; Jauch and Watzka, 2012).

While many papers focus on developed countries due to their data reliability and completeness, this paper gives considerable attention to emerging markets while also exploring a diverse sample of 82 low- and high-income countries. In this regard, we investigate how differently are the effects of financial development on inequality in emerging markets, compared to non-emerging ones. Therefore, taking a cross-sectional approach, using both OLS and 2SLS methods, our findings show that most of the financial development indicators increase the growth of income inequality, and this effect is more alarming in developed countries. Most of our results also show that emerging markets still benefit from a more developed financial system, as seen from their lower levels of inequality.

Keywords

Financial Development Dimensions, Income Inequality Measures, Disposable and Market Gini Coefficient, Gross and Net Income Inequality, SWIID

[§] This essay was prepared for *FGDB Costin Murgescu Contest - 2020 Edition* and it contains 25 pages excluding front page and bibliography.

[‡] University of Oxford, DPhil Candidate in *Geography and the Environment* (Economy and Society, Transformations and Justice Research Cluster).

1. Introduction and Literature Review

In the aftermath of the 2008-2009 financial crisis, public opinion started to question how beneficial is the contribution of the financial system on our economy and society. Recent evidence from Piketty (2014) reveals the propensity of contemporary financial capitalism to increase income inequality. According to the OECD report (2016), *"income inequality remains at record-high levels in many countries despite declining unemployment and improving employment rates".* In this context, Atkinson (2015) proclaimed that concentrating the wealth in the hands of a few attracts negative socio-economic consequences while Yunus and Weber (2017) claimed that income inequality threatens *"human progress, social cohesion, human rights and democracy".* This is why, paraphrasing Lagarde (2015), decreasing excessive income inequality *"by lifting the small boats"* is not only morally and socially right, but also beneficial for the economy.

Although a growing body of literature has investigated the relationship between financial development and economic growth, less concern has been raised regarding a more intriguing question, namely the finance-inequality nexus. When assessing this relationship, the reader must be aware that the literature abounds with a plethora of conflicting views (Demirguc-Kunt and Levine, 2009), caused by significant differences in finance dimensions (deHaan and Sturm, 2017) and inequality measures, as well as by methodologies used. In this paper, our purpose is to understand financial development, its detriments and impact on income inequality in a macro analysis of a large and diverse set of countries. As defined by Fernandez and Tamayo (2017), financial development is *"the process by which financial system ameliorates (or eventually overcomes) information and enforcement frictions, as well transaction costs, in order to facilitate trade, mobilize savings and diversify risk"*. Since it is not an immutable phenomenon, it makes common sense to question its impact on inequality. At the moment, the landmark literature makes use of three different hypotheses to explain the finance-inequality nexus (Clarke *et al*, 2006), as seen in Table1.

TABLE 1. Financial Development Hypothesis. Source: Clarke *et al*, 2006.

Hypothesis	*Description*
Inequality-narrowing hypothesis	Finance access improvements reduce inequality and benefit low-income households in both poor and wealthy countries.
Inverted U-shaped hypothesis	At the beginning, finance access improvements aggravate inequality in poor countries. A certain stage of financial development is required in order to improve inequality.
Inequality-widening hypothesis	Financial development exacerbates the already high-inequality existent in some countries.

Inequality-Narrowing Hypothesis of Financial Development. Previous research has found that financial development can facilitate the enhancement of economic growth and respectively the alleviation of inequality and poverty. In their two-sector linear model, Galor and Zeira (1993) demonstrated that in the presence of credit-market imperfections, income and wealth distributions have a significant effect on the macroeconomic activity (respectively investments, skilled/unskilled labour and output). In general, only agents who bequest large human capital investments from past generations can borrow and make investments, as well as work in skill-intensive industries. Consequently, in the absence of a large enough middle class, this mechanism perpetuates income inequality and slows down economic growth (*ibid*). Banerjee and Newman (1993) share a similar belief that capital-market imperfections and initially-unequal wealth distribution trigger less borrowings for indivisible investments. Thus, occupations that require great investments are less accessible for the poor people, whose ultimate fate is to work for more wealthy employers. By contrast, less extreme poverty will converge towards a more prosperous high-salary and high-employment economy (*ibid*). Simply put, financial development can either bring about what Banarjee and Newman (1993) call the cottage industry (through self-employment) or factory production (through employment contracts).

Moreover, Li, Squire and Zou (1998) claim that rich people can easily exercise their power, resources and influence over the economic policy in order to maintain their wealth and benefits. In contrast, capital market imperfections restrict the poor to accumulate capital. Thus, these two channels, and particularly the latter one, reinforce unequal income distributions. They also argue that inequality presents a stable pattern within countries, but fluctuates considerably among countries (*ibid*).

According to Beck, Demirgüç-Kunt and Levine (2007), and Hamori and Hashiguchi (2012), financial development reduces inequality by stimulating income growth in the poorest quintile. Moreover, they claim that decreasing credit constraints, allocating resources efficiently and allowing all agents to participate in the credit markets benefit deprived people more than the rich, either disproportionately (Beck *et al*, 2007) or proportionally (Hamori and Hashiguchi, 2012). A strong argument for this is that credit constraints trigger inefficient capital allocation and intensified income unbalances (Aghion and Bolton, 1997; Galor and Zeira, 1993; Galor and Moav, 2004). Similarly, in their cross-sectional and panel data research, Kunieda, Okada and Shibata (2014), showed that the relaxation of credit market imperfections triggers an increase in the borrowing demand and thus in the equilibrium interest rate. Consequently, income inequality narrows down. But their research gets more intriguing when they find out that financially-closed economies are more prone to narrow their inequality as a result of a more developed domestic financial market. Clarke, Xu and Zou (2006) conducted a panel analysis and found a negative linear relationship in support of the narrowing-hypothesis, showing that the more developed the markets are, the less financial friction and therefore the lower the inequality levels. Hence, the more efficient the financial system, the more productive and fairer the capital allocation. However, we must be aware that risky and speculative misallocations may put this into danger (Diamond, 2016).

Zhang and Naceur (2019) conducted a multidimensional investigation of 10 different financial development indicators for both financial institutions and markets. Their results reveal that almost all bank and stock market indicators reduce income inequality. Kappel (2010) also gives consideration to both loan markets and stock markets. Her cross-country and panel data regressions indicate that both dimensions of financial development can reduce inequality. However, as seen in Appendix1, most of the studies mainly focus on the financial development of the banking system. This is understandable since this data is generally available for most of the countries and over sufficiently long periods. Additionally, there is a general opinion among scholars that the impact of finance on inequality is channelled mainly through the banking sector rather than the stock markets (Kappel, 2010; Gimet and Lagoarde-Segot, 2011; Naceur and Zhang, 2016).

Inverted U-shaped Hypothesis of Financial Development. There are some neutral works which take into consideration the dual effect (non-linear relationship) of financial development on income inequality. Starting from Kuznets's (1955) pioneering work on the inequality-development nexus, we expect that during an economy's lifespan, inequality increases in the first stage of development, becomes gradually weaker in the juvenile stage and shrinks in the mature stage. Based on the literature, Greenwood and Jovanovic (1990) suggest more supporting evidence from Lindert and Williamson (1985) who found a striking example of Kuznets Curve in the British history from 1688-onwards. Therefore, the British Industrial Revolution triggered a rising income inequality whereas the end of the nineteenth century experienced a lengthy levelling. Furthermore, Paukert (1973) and Summers, Kravis and Heston (1984) examined within-country income inequality in the context of economic development. The latter discovered that in 1950-1980 inequality fell in industrialized countries and increased for low-income countries. Moreover, Greenwood and Jovanovic's endogenous growth model (1990), which takes into consideration the financial sector development effect on inequality, reaches the same conclusion of a hump relationship between the two variables.

Based on the assumption that poor people accumulate wealth more slowly, discrepancies between the incomes of rich participants in intermediary coalitions and those of poor outsiders will broaden. On one hand, the fixed coalition membership fee will prevent poor agents from joining. On the other hand, the fixed fee will encourage all agents to take part in financial coalitions, decreasing the initial upward trend of inequality. Thus, Greenwood and Jovanovic (1990) say that regardless of the stage of economic development, financial development has a positive impact on capital allocation, aggregate growth and ultimately on the poor. Still, the wealthy are the only ones who directly benefit from better financial markets in the very early stages of development, as well agreed by Beck *et al* (2007).

The literature has also been enriched with recent studies of this non-linear relationship. For instance, in his work, Nikoloski (2012) questioned a simple linear relationship between finance and inequality, confirming instead the existence of the Kuznets curve and the inverted-U curve hypothesis elaborated by Greenwood and Jovanovic (1990).

Kim and Lin (2011) found that financial development is beneficial to inequality reduction once the countries reach a threshold level of financial development. Furthermore, research by Law, Tan and Azman-Saini (2014) points out that the finance-inequality nexus varies with different threshold levels of institutional quality.

Suspecting that the other studies suffer from aggregation bias, Bahmani-Oskooee and Zhang (2015) conducted a unique time-series analysis, showing that 10 out of 17 countries from their sample presented an equalizing effect of financial development on inequality in the short-run. However, this equalizing effect – which would involve the majority of the people to freely borrow funds for education or business - maintained only in 3 countries in the long-run.

More recently, Tan and Law (2014) found out a normal U-shape between financial depth and income inequality (when using the measure elaborated by Solt, 2008), implying that the latter one can narrow down in the early stages of financial development, but only below a specific threshold level of financial deepening, otherwise it will worsen off. Simply put, both the poor and the rich can access the financial markets in the beginning of their development process. Later on, financial markets will become inefficient and thus the income inequality will widen.

Inequality-Widening Hypothesis of Financial Development. There are many economists, just like Rajan and Zingales (2014), who question whether finance inordinately favours the wealthy. In this regard, we bear in mind the Marxist theory that usually portrays greedy financiers who serve the needs and hidden interests of the rich whereas the poor are left apart, primarily accessing capital through relatives and other informal means. More and more researchers have recently reported that financial development fuels higher levels of income inequality (Jaumotte *et al*, 2013; Denk and Cournede, 2015). Gimet and Lagourde-Segot (2011) measured the effect of size, efficiency and integration of financial institutions and capital markets on inequality. Their results indicate that crony domestic banks can be a real menace to equality, having a stronger effect than stock markets. Jauch and Watzka (2016) also found a highly-significant and positive finance-inequality relationship within their sample countries, which holds for robustness checks. However, they admit that the coefficient of financial development is of a small magnitude: the Gini coefficient will increase on average by 0.22 for the within estimation if the credit provision increases by 10%.

Recent research by deHaan and Sturm (2017) show that income inequality widens with a higher degree of financial development. This positive relationship between financial development and income inequality is not conditioned by democratic accountability, in contrast to the findings of Rajan and Zingales (2003), who claim that high-quality institutions promote an inequality-narrowing effect of finance on inequality. However, some caution must be taken when analysing deHaan and Sturm's (2017) findings, mainly because their income inequality measure is based only on gross income. Ultimately, they completely ignore (on purpose) redistribution policies.

2. Methods and Data

Our empirical work consists in a cross-country model specification using Ordinary Least Squares (OLS). The reasoning behind the choice of cross-sectional data in our analysis can be found in its utility for assessing the relationship between income inequality and financial development by studying differences across countries during a specific time-period (Stock and Watson, 2015), and for evaluating existent economic policies (Wooldridge, 2013). According to Clarke, Xu and Zou (2006), a cross-sectional analysis proves useful when the researcher's interest is to capture the long-term relationship between financial development and inequality and, thus to test this relationship in the inequality-narrowing and inequality-widening hypotheses, which we would like to do in our analysis as well. Therefore, we estimate a growth regression specified as:

$$Ineq_i = \beta_0 + \beta_1 FD_i + \beta_2 X_i + \varepsilon_i \qquad (1)$$

where $Ineq_i$ represents our chosen income inequality indicator, namely the growth of the Gini coefficient, FD_i represents one of the financial development indicators, X_i refers to all control variables and lastly ε_i shows the error term. *i* refers to each country in the sample. Since we aim to assess 7 different financial development indicators, we will also have 7 different models. In this analysis we use averaged data from 1995 to 2014 for 82 countries, classified as developed, non-developed and emerging countries (EM).

$$Ineq_i = \beta_0 + \beta_1 FD_i + \beta_2 (FD * EM) + \beta_3 X_i + \varepsilon_i$$

Based on MSCI classification, we created an extra variable - an interaction between each financial development indicator and a dummy which indicates whether the country is an EM or not. Following the above equation, our regression results can show whether and how differently financial effects on inequality behave in EM. For example, if β_2 turns positive, FD has a more widening-effect on inequality in EM compared to non-EM.

Given the endogeneity problem of financial development, extreme caution must be taken when performing regressions. To address this problem, we apply the methods of instrumental variable (IV) estimation and two stage least squares (2SLS).

Endogeneity issues may be associated with reverse causality from income inequality to financial development, omitted variables bias (unobserved heterogeneity), self-selection, simultaneity and errors-in-variables (Wooldridge, 2013). In terms of reverse causation, for instance, less income inequality might mean increased affordability of the poor to access financial services, and consequently better development of the financial system. Similarly, a lower level of income inequality might stimulate economic growth, as suggested by the inverted-U shape of the effect of income distribution on economic growth (Zhang and Naceur, 2019). Therefore, it is absolutely necessary to control for possible endogeneity issues and reversed causation when using financial variables and GDP per capita. Based on the theory, we can employ some instrumental variables on law, finance, growth (Clarke, Xu and Zou, 2006), ethnic fractionalization, linguistics or religious composition (Zhang and Naceur, 2019).

Equations (2) and (3) exhibit the 2SLS models. We included in our base model one additional variable z_1 which is closely correlated with the Financial Development indicator, but not with the Income Inequality measure, the residual term v and the error term ε. Depending on each Financial Development measure and the most favourable regression results, we chose instruments like Legal Origin, Protection of Property Rights or Religious Fractionalization. We also considered other instrument variables like the Ethnic and Linguistic Fractionalization index (Alesina *et al*, 2003) or the indexes for Judicial Independence and Impartial Courts from the Economic Freedom Dataset (2018), but they do not deliver the expected results, therefore they are not reported in this paper. The purpose of these instruments is to approximate financial development and to use this approximation to model the Inequality growth rate.

Reduced-Form (First-Stage): $$FD_i = \alpha_0 + \alpha_1 X_i + \alpha_2 z_1 + v \quad (2)$$

Structural Model (Second-Stage): $$Ineq_i = \beta_0 + \beta_1 \widehat{FD}_i + \beta_2 X_i + \varepsilon \quad (3)$$

Furthermore, this paper aims to verify the following hypotheses:

H1: *Financial Development has a widening-effect on Income Inequality.*

H2: *Financial Development has a more narrowing-effect on Income Inequality in emerging countries than in developed (non-emerging) countries.*

Our Gini data is downloaded from the SWIID database (Solt, 2019) and comes in net (disposable) and gross (market) household values. According to deHaan and Sturm (2017), the net Gini coefficient is more heavily influenced by the redistribution process via taxation. Therefore, the gross index based on pre-taxes households is a more reliable proxy for income inequality (*ibid*). However, income distribution (as quantified by the gross Gini coefficient) is also affected by taxes and government expenditures (Bergh, 2005). For comparability purposes, we decided to use both net and gross Gini coefficients since they may differ considerably due to different redistribution policies.

The comprehensiveness and comparability characteristics of the SWIID database, as a reason of its standardized income values, have been acknowledged by Delis, Hasan and Kazakis (2014). However, this dataset also imputes missing values. Solt (2009) considers that this *"represents a particular choice in the balance between comparability and coverage: it maximizes comparability for the broadest available set of country-year observations"*. This is because most of developing countries suffer from paucity of data, thus we must account for possible uncertainties in the estimates.

Most of the studies on the topic use the WIID - World Income Inequality Database, which presents some inconveniences though: missing data and multiple Gini values for the same country/year. Furthermore, deHaan and Sturm (2017) showed that the available number of Gini observations is much lower in the case of WIID and it cannot differentiate between net and gross Gini coefficients, which can show negligent research about the theoretically-relevant variable (Solt, 2015). From this point of view, SWIID proves to be more reliable, providing annual observations which are multiply-imputed (Jenkins, 2015). Therefore, with this paper, we align ourselves in the currently increasing cohort of the more recent research which uses the SWIID updated database. Furthermore, we believe that taking a pure cross-sectional approach with data averaged over the 1995-2014 period is a more efficient method compared to the one used by Beck *et al* (2007). In their analysis, the growth of the Gini coefficient was attained by dividing the log difference of the first and last data point over the time period used. It is understandable why they took this approach since their WIID dataset (developed by Dollar and Kraay, 2002) suffered from missing values, which is not our case using the SWIID database.

Financial Development Indicators. Since the existing literature focused its attention mainly on the financial deepening, we believe that this approach does not provide a complete investigation on the relationship between financial development and income inequality. Therefore, this paper takes a multidimensional investigation in line with the unique approach of Zhang and Naceur (2019). Mainly, we seek to analyse four different dimensions of financial development (as elaborated by Cihak *et al*, 2012), specifically access, depth (financial deepening), efficiency and stability of both financial institutions and financial markets, downloaded from the Global Financial Development Database.

We firstly consider the **Access** to financial services measured as Bank accounts per 1000 adults and Value traded excluding the top 10 companies to the total value traded. The higher the values of these measures, the easier the access to banks, respectively financial markets. Belley and Lochner (2007) emphasize on the benefits of credit market access on investments in education and on the alleviation of school abandonment when the family faces income crisis. Unfortunately, data availability dictates our choice to drop the measure of Bank accounts and only consider the Value traded. Kim and Lin (2011) state that Value traded is a measure of the market trading (without the top companies) compared to the size of the economy. Cihak *et al* (2012) claim that these scant measures of financial access provide an estimation of the breadth of use of finance through available institutions and instruments.

TABLE 2. Variables, Description and Measurement.

	Variable	*Description and Measurement*
	Dependent Variable – Income Inequality Indicator - Source: SWIID	
	Growth of Gini Coefficient *(ginidg and ginimg)*	The growth of the Gini Coefficient was calculated for a sample of 20 years, taking the average of their annual growth rate.
	Independent Variables of Interest – Financial Development Indicators – Source: World Bank GFDD	
ACCESS	**Bank accounts/1000 adults** *(Not included)*	Number of deposit account holders at commercial banks per 1000 adults. Calculated as the number of depositors divided by the adult population of the respective country, multiplied by 1000.
ACCESS	**Value traded excluding the top 10 trading companies to total value traded** *(Value)*	Value of all traded shares (except for those of the top ten largest companies) to the total value of all shares traded on a stock exchange market. The variable is aggregated until the country-level using a simple average over exchanges.
DEPTH	**Private credit to GDP** *(Credit)*	Claims on the private sector by deposit-money banks and other financial institutions to GDP
DEPTH	**Stock market's total value traded to GDP (%)** *(SMV)*	Total value of all shares traded on a stock exchange market to GDP
EFFICIENCY	**Net interest margin** *(Interest)*	Accounting value of the net interest revenue as a share of the average interest-bearing assets of banks.
EFFICIENCY	**Stock market turnover ratio** *(SMTR)*	Ratio of the total value of traded shares to the average real market capitalization
STABILITY	**Regulatory capital to risk weighted assets** *(RegCap)*	Ratio of the total regulatory capital of banks to the assets held by those banks. It is weighted in accordance with the risk borne by the assets. Shows the level of capital adequacy of deposit-money banks.
STABILITY	**Volatility of stock price index** *(Volatility)*	Average price volatility of the national stock market index over 360 days.

Note: *Stata variables' names reported in parenthesis for the ease of language. All FD variables enter our regressions in level form after they have been averaged for 1995-2014 period. The two Gini coefficients have been transformed in annual growth rates which have been averaged afterwards for the respective period.*

Financial Depth was measured using as indicators Private credit and Stock market's total value traded to GDP. The higher the values of these indicators, the deeper the financial system. The rationale behind choosing Private credit to GDP as a proxy of financial development stands in its ability to measure an essential function of financial intermediaries, namely channelling public savings to the private sector (Beck *et al*, 2007), a feature that other measures, such as M2 (broad money) over GDP, do not have (*ibid*; deHaan and Sturm, 2017). Hence, unlike M2 to GDP, Private credit does not take into consideration the credit to central or development banks and public enterprises, thus it is a "cleaner" measure of the financial sector (Beck *et al*, 2007; Clarke et al, 2006). Another measure we considered was the ratio of commercial banks' assets to the sum of the assets held by both the central and commercial banks (developed by King and Levine, 1993; Dollar and Kraay, 2002). However, this measure may not catch the whole cross-country variation in financial development since in some states the central bank does not have a key role in the credit allocation and commercial banks do not represent the only financial intermediaries of a society (Beck *et al*, 2007). Correspondingly, our choice of Private Credit as a proxy of financial development was strongly supported by previous literature (Beck, Levine and Loayza, 2000; Levine, Loayza and Beck, 2000) showing its robust-positive effect on GDP/capita growth, and its ability to measure the ease with which new firms and entrepreneurs can finance their projects (Rajan and Zingales, 2003).

In terms of **Financial Efficiency**, we chose the Net interest margin. The higher its values, the lower the operating efficiency of financial institutions, the less competition and the higher the level of market imperfections. Stock market-turnover ratio was selected to show the efficiency of financial markets which increases together with the ratio. According to Kim and Lin (2011), the turnover ratio is an indicator of stock market liquidity, measuring the trading volume of the stock market compared to its size. Casti (2018) argues that the more inefficient the financial system is, the higher the level of inequality.

Lastly, we measured **Financial Stability** by the Regulatory capital to risk weighted assets ratio and respectively the Volatility of the stock price index. The higher the Regulatory capital, the lower the default risk of a bank, whereas the higher the Volatility, the higher the instability of the financial market (Zhang and Naceur, 2019).

In line with previous studies on economic growth and income inequality determinants, some control variables were added to our model: GDP per capita growth, population growth, inflation, government consumption, trade openness, initial schooling, initial Gini and age dependency ratio. Though uncertain about their effects on inequality, we expect the coefficient on GDP per capita growth to be negative because the lower the inequality, the higher the income level (Zhang and Naceur, 2019). Likewise, trade openness and government consumption coefficients are expected to be negative based on the benefits that international openness and public spending can bring to the society. Moreover, as stated by Easterly and Fischer (2001), we expect a positive coefficient on inflation since it hurts the poor people more than the rich. The effect of school attainment and age dependency ratio on income inequality might vary considerably from country to country.

Lastly, as inequality changes slowly over the years, we use the initial Gini to capture the catch-up effect because some economies, and thus their Gini coefficients, grow faster than others, so we want all our countries to eventually converge.

<u>Descriptive Analysis.</u> The table below illustrates the descriptive statistics of our variables for the total sample. Starting the statistical interpretation with our 7 financial development indicators, we can see that DM perform better financially than EM. For instance, on average, DM have higher ratios of Value traded (excluding top 10 trading companies) to total value traded, therefore in DM people have easier access to financial markets than in EM (47% > 44%). In our sample, the country which has the most restrictive access to financial markets is Hungary (2.93%), followed mainly by Latin American countries. This does not come as a surprise since only the top 3 trading companies on the Budapest Stock Exchange index have a weight of 86.19% (BSE, 2019). In terms of the highest levels of stock market access, as expected, we find some of the most developed countries: USA, Canada and Japan.

TABLE 3. Descriptive Statistics of the Main Variables.

Stata Code	*Countries*	*Mean*	*Min*	*Max*	*SD*	*Skew*	*Kurt*	*Obs*
Gini Disposable Growth		**0.02**	**-0.91**	**1.05**	**0.50**	**-0.09**	**2.20**	**82**
Gini D	EM	-0.17	-0.91	0.82	0.49	0.45	2.45	20
	DM	0.23	-0.44	0.87	0.31	0.09	2.74	23
Gini Market Growth		**0.03**	**-0.95**	**1.10**	**0.43**	**-0.19**	**2.67**	**82**
Gini M	EM	-0.07	-0.95	1.10	0.48	1.44	3.27	20
	DM	0.23	-0.08	0.64	0.18	0.06	3.00	23
Value Traded		**45.69**	**2.93**	**75.72**	**19.74**	**-0.26**	**2.29**	**31**
Value	EM	44.15	2.93	73.69	17.24	-0.54	3.84	14
	DM	47.92	14.03	75.72	21.02	-0.24	1.59	13
Private Credit to GDP		**60.70**	**6.51**	**172.87**	**44.61**	**0.81**	**2.60**	**80**
Credit	EM	51.26	14.77	126.91	36.06	1.02	2.55	20
	DM	111.19	64.48	172.87	31.50	0.45	2.33	22
Stock Market Total Value		**33.13**	**0.01**	**337.67**	**52.33**	**3.40**	**18.26**	**71**
SMV	EM	21.34	3.61	57.62	15.75	0.80	2.54	20
	DM	75.28	8.27	337.67	71.92	2.30	8.91	23
Net Interest Margin		**4.34**	**0.76**	**12.65**	**2.82**	**0.99**	**3.59**	**79**
Interest	EM	4.43	2.07	7.10	1.54	0.30	1.87	20
	DM	1.67	0.83	3.66	0.63	1.20	5.29	23
Stock Market Turnover		**49.51**	**1.22**	**181.52**	**46.81**	**1.32**	**4.05**	**69**
SMTR	EM	57.12	11.28	181.52	51.80	1.52	3.97	20
	DM	75.61	20.74	164.11	36.18	0.60	3.01	23
Regulatory Capital		**14.71**	**10.78**	**25.64**	**2.57**	**1.41**	**6.88**	**59**
RegCap	EM	14.88	12.10	19.52	2.10	0.84	2.82	19
	DM	13.31	10.78	17.01	1.62	0.29	2.68	22
Volatility Stock Price Index		**22.67**	**11.14**	**42.22**	**5.99**	**1.08**	**4.97**	**51**
Volatility	EM	26.63	17.63	42.22	6.85	0.84	2.94	19
	DM	20.02	12.06	27.30	3.62	-0.15	2.72	23

Note: *The highlighted rows represent the total for the sample. For the full name of variables, check the table from Sub-section 3.2.2. All variables for each country are averaged for the period 1995-2014. Except for the Gini coefficients, which were transformed in annual growth rates and then averaged, all variables enter regressions in their level form. EM=Emerging Markets; DM=Developed Markets.*

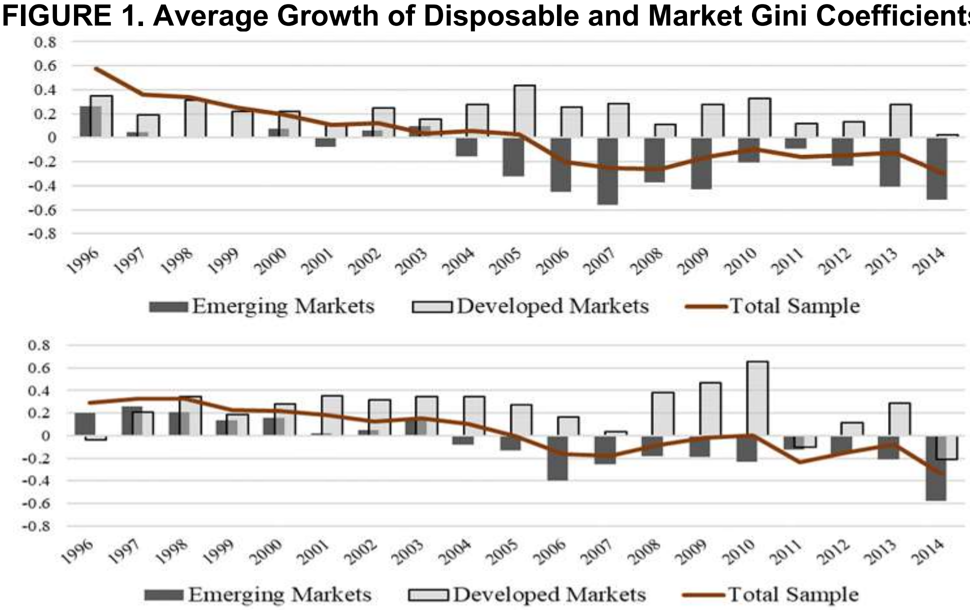
Regarding the financial deepening dimension, our sample encounters wide variations across countries in Private Credit, and respectively Stock market total value traded to GDP (SMV). Taking a bird's eye view, DM have on average a financial system double in size than the one of EM, and a stock market 3 times deeper/bigger (see average total Mean 75.28%>21.34%). Among the countries which channel the highest amounts of public savings to private projects are Japan (with a ratio of 172.87%), USA, Hong Kong and Canada, while on the other end of the spectrum we find Latin American EM like Argentina (with a ratio of only 14.47%). However, our total sample includes African countries with even lower ratios: Malawi (6.51%) and Tanzania (7.58%). According to Sacerdoti (2005), African countries' modest credit expansion is a consequence of the unsupportive institutional framework, inadequate and limited information, weak accounting standards and lack of collateral registration. Also, Latin American countries experienced declines in private credit after the mid-1990s banking crisis, exacerbated by weak regulation and poor bank management (Jeanneau, 2007). Though slightly increasing, the 1990s values have not yet been reached nowadays (*ibid*). Furthermore, these countries also face very low SMV ratios (0.01% in Uruguay and 3.61% in Peru).

Moving on to the efficiency dimension of FD, we notice that EM financial institutions are characterized by lower average operating efficiency compared to DM (4.43% > 1.67%). Again, from our sample of EM, Latin American ones have the least efficient banks, though African countries like Malawi (12.65%) show even lower efficiency levels. At the opposite side, Ireland (with 0.8% - see Min column for Interest DM) has a top-tier banking system in terms of efficiency, competition and low levels of market imperfections. As expected, regarding the stock market, DM perform more efficiently on average (75.61%>57.12%). Surprisingly, there are also some EM (like Pakistan, Turkey, China, Thailand) which performed remarkably above the mean of DM (75.61%). The maximum in our sample is 181% (Pakistan). However, since this is an average of all the values from 1995 to 2014, we must be cautious and understand that Pakistan had extremely high turnover ratios in the beginning of 2000s. From the best stock market performance in the world, nowadays Pakistan's stock market turnover ratio is under the average of EM (see Mean EM SMTR 57.12%), being affected by the country's political and economic crisis. On average, there are also EM that have low SMTR, mostly Latin American.

Lastly, regarding the stability of the financial system, we can see that, on average, EM have slightly higher Regulatory capital to risk-weighted assets (RegCap) ratios (14.88%.13.31%), meaning that their banks are less prone to default risks. Moreover, in terms of minimum and maximum, EM also show higher ratios (minimum 12.10% in Greece and maximum 19.52% in Turkey) whereas DM show a maximum of 10.78 in Australia and 17.01 in Singapore. We suspect this is because EM have tighter lending standards and loan monitoring compared to DM (Cihak *et al*, 2012). In what concerns the financial markets, EM face more instability, as shown by the slightly high mean Volatility ratio (26.63%>20.02). Moreover, their overall distribution is moderately and positively-skewed (0.84), meaning that most of the EM experience financial instabilities, ranking with Russia (42.22%) and Turkey (39.53%).

We will now continue with the interpretation of our chosen Income Inequality indicators: Gini Disposable and Gini Market. The mean growth rates of the Gini coefficients show that in general the market Gini coefficient grows, on average, faster than the disposable one (0.03>0.02). In general, EM exhibit a negative average growth of the Gini coefficient, meaning that inequality might have slightly fallen, though being still present in these countries. This decrease is even more accentuated for the after-taxes Gini coefficient (Gini-Disposable = -0.17 versus Gini-Market = -0.07). On the contrary, DM exhibit a positive growth of Gini coefficients, which can be translated in an increase in inequality.

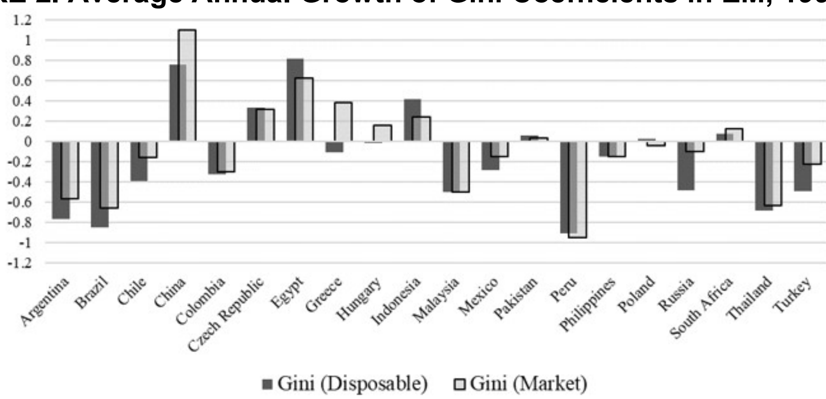
FIGURE 1. Average Growth of Disposable and Market Gini Coefficients.



Since a negative growth rate of the Gini coefficient is our desirable effect, we can see that, on average, EM pursue a trend of accelerated decrease in the values of the Gini coefficients from 1996 to 2014. This is understandable since the current EM usually started with very high base values for inequality, reducing them only from 2004 onwards. In parallel, DM had already-low Gini coefficients at the starting point of our research period, and thus lower levels of inequality. These trends can be seen for both disposable and market Gini (Figure 1). Interestingly, only in 2011 and 2014 the growth of market Gini coefficient turned negative for DM as well.

Looking at each country in detail (Figure 2) and comparing their average annual growth of the Gini coefficients (1995-2014), in our EM sample, China presents the highest average annual growth rate of the inequality coefficient while Latin American countries (Argentina, Brazil, Chile, Colombia, Mexico, Peru) together with Malaysia, Philippines, Thailand and Turkey exhibit a negative average annual growth rate of their Gini.

FIGURE 2. Average Annual Growth of Gini Coefficients in EM, 1995-2014.



However, when it comes to DM, what strikes our attention are the negative average annual growth rates of the disposable (net) Gini in comparison to the positive ones of the market (gross) Gini, especially in Ireland and Switzerland. An explanation would be the fact that, for instance, Ireland applies one of the highest and most favourable tax relief rates in Europe. Therefore, people with disabilities, single parents or older people, just to name a few examples, can reduce the amount of tax they pay through tax credits, allowances and standard-rate cut-off points. Still, living in a well-developed country comes with a cost that the poor cannot afford, as seen from the countries with the highest average annual growth rates: Denmark, Finland, Germany, Norway, Sweden or USA.

FIGURE 3. Average Annual Growth of Gini Coefficients in DM, 1995-2014.

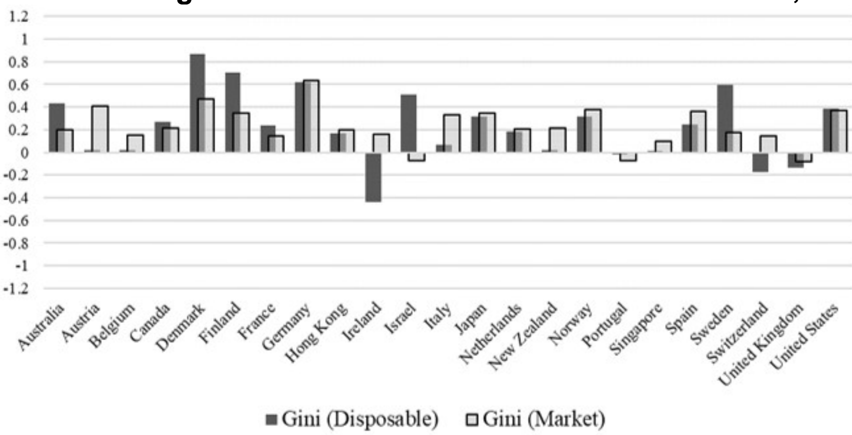
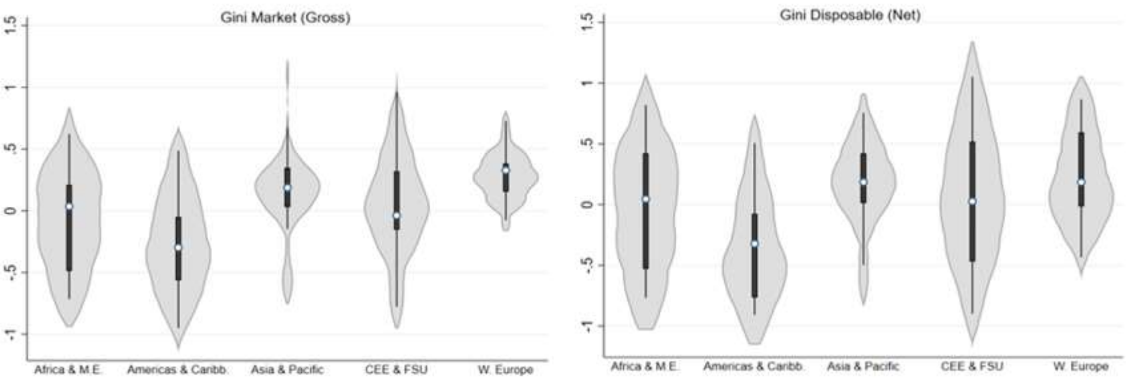


FIGURE 4. Violin Plots of Gini Growth (Market and Disposable) Based on Regions

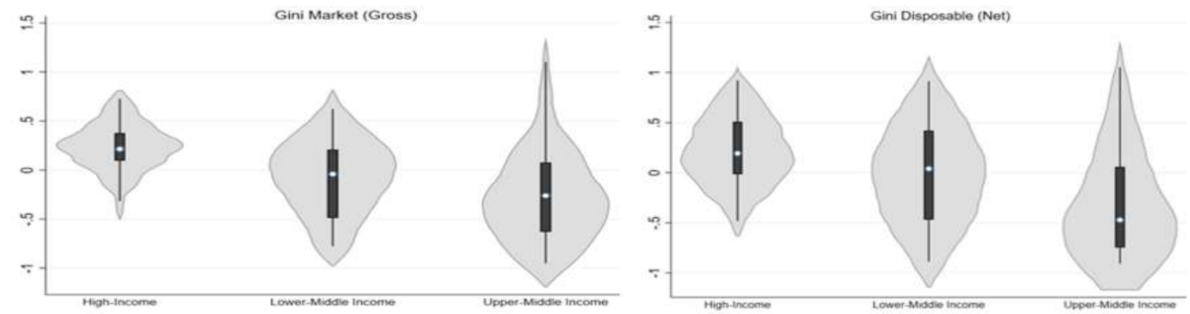


Note: *Countries are classified in 5 regions: Africa and Middle East; (Latin and North) America and Caribbean; Asia and Pacific; Central-South Eastern Europe and Former Soviet Union; Western Europe. The complete list of countries can be found in Appendix.*

Since geographically-clustered countries may share a high degree of commonality, we believe that a regional analysis of our income inequality measure would trigger even more insights in what is the real situation before and after taxes (Figure 4). African and Middle East countries' distribution shows that most of the countries in our sample experience a decrease in Gini coefficient growth, even though there are still countries with increasing inequality. Unsurprisingly, Americas and Caribbean countries (mainly because of Latin American ones) present the most considerable declines in the average growth rate of both Gini-M and Gini-D coefficients, even though Latin America faces among the highest levels of inequality. Asia and Pacific show a high density between 0 and 0.5, meaning that most of the countries have a positive growth of both pre- and post-taxes income inequality. According to Hassell (2018), some countries from Eastern Europe faced increasing levels of inequality in the post-Soviet period, after 1990s. From our sample though, we can see that most of them are still at the limit between no change and modest changes in the growth of inequality. Lastly, Western Europe has a very concentrated distribution of countries with high positive growth rates in inequality before taxes. However, after taxes, this distribution widens.

The situation is different when we analyse grouped countries based on income level (Figure 5). High- and lower-middle income countries have a quite symmetric distribution whereas upper-middle income countries have a right-skewed distribution. This means that most of the upper-middle income countries experience high decreases in their Gini. Conversely, high-income countries face the highest average growth rates of inequality.

FIGURE 5. Violin Plots of Gini Growth (Market and Disposable) Based on Countries' Income Level (World Bank).



Note: Lower-Middle income distribution also contains 4 countries initially classified as Low-Income countries. This is because we wanted to avoid their exclusion from the sample.

TABLE 4. Pearson Correlation Matrix and Normality Test.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
(1) Gini Disposable	1								
(2) Gini Market	0.88	1							
(3) Value	0.12	-0.09	1						
(4) Credit	0.20	0.29	0.33	1					
(5) SMV	0.19	0.20	0.41	0.65	1				
(6) Interest	-0.37	-0.40	0.03	-0.71	-0.39	1			
(7) SMTR	0.31	0.36	0.39	0.41	0.51	-0.37	1		
(8) Reg Cap	-0.31	-0.29	-0.01	-0.42	-0.16	0.51	-0.35	1	
(9) Volatility	-0.26	-0.17	0.14	-0.43	-0.05	0.38	0.22	0.45	1
Normality Test	No	Yes	Yes	No	No	No	No	No	

Note: Normality Test for Normal Distribution assesses the skewness and kurtosis of the variables (D'Agostino, 1990). The Gini (Disposable and Market) refer to average annual growth values.

Regarding the relationship between FD and income inequality, Table 4 reports the Pearson correlation matrix of the 7 financial variables with the Growth of the Gini coefficients. Some of the FD indicators are positively-correlated and others negatively-correlated with the growth of the Gini coefficients. Therefore, we expect mixed findings from our regression tables.

3. Empirical Results

<u>Financial Deepening and Income Inequality.</u> The table below reports the robust results where the FD coefficients are both positive and significant in both OLS and 2SLS models (Columns 1 and 2). Firstly, the OLS results indicate that 1% increase in the Private Credit to GDP (Credit) and respectively in Stock Market Value Traded to GDP (SMV), can trigger an increase of 0.002% in the growth of the Gini coefficient based on disposable (net) income (Gini D), *ceteris paribus*. This translates in an increase in inequality. This equal effect of both financial institutions' depth (measured by Credit) and financial markets' depth (measured by SMV) surprisingly contradicts what the majority of the literature says, namely that stock market development has a lower impact on inequality in comparison with credit market development (Kappel, 2010). Unsurprisingly, the results for Gini M (Column1) confirm this argument: in comparison with SMV, an increase in Credit triggers a 3-times higher increase in Gini M growth. When comparing results for Gini D and Gini M, we find out that financial depth indicators have a higher impact on the growth of the Gini M coefficient, meaning that they accelerate the growth of income inequality before taxes. An explanation would be that the Gini coefficient based on market (pre-taxes) income shows the ugliest side of income inequality while the Gini based on disposable (post-taxes) income shows a more realistic level of inequality. This is because many countries adopted a progressive tax system in which the average tax rate increases with the taxable amount. For instance, in the USA, the top richest 1% contribute with 37% of the revenues coming from the totally-collected income tax whereas the bottom 50% contribute with less than 3% (Roser and Ortiz-Ospina, 2016).

TABLE 5. Effects of Financial Depth of Income Inequality

Financial Depth	*GINI DISPOSABLE*			*GINI MARKET*		
	OLS (1)	*2SLS* (2)	*OLS Interaction* (3)	*OLS* (1)	*2SLS* (2)	*OLS Interaction* (3)
Credit	0.002*	0.005***	0.002*	0.003**	0.006***	0.003**
Credit*EM			-0.001			-0.000
R-Squared	**0.528**	**0.506**	**0.529**	**0.423**	**0.370**	**0.423**
Observations	**76**	**75**	**76**	**79**	**78**	**79**
SMV	0.002***	0.004*	0.002***	0.001*	0.006***	0.001*
SMV*EM			-0.0004			0.002
R-Squared	**0.453**	**0.415**	**0.453**	**0.388**	**0.149**	**0.392**
Observations	**71**	**71**	**71**	**70**	**70**	**70**

In most cases, the Durbin-Wu-Hausman Test fails to accept the null hypothesis that FD variable is exogenous, meaning that we deal with endogeneity issues. Thus, Column2 of both tables show that after controlling for endogeneity, using the 2SLS method and the Protection of Property Rights index as an IV, the coefficients of Credit and SMV remain not only statistically significant and positive, but they almost double in size (Column2 of both tables). The Sargan-Hansen J-Test and the Partial F-statistics Test confirm that Protection of Property Rights index is a strong instrument for Credit, but not for SMV.

In line with deHaan and Sturm (2017) and Jauch and Watzka (2016) who used exactly the same dependent and independent variables from the same sources (namely the Gini coefficients from SWIID database and Private Credit to GDP), our results confirm the inequality-widening hypothesis of FD. However, in contrast with these studies, we opted for a cross-sectional data analysis. deHaan and Sturm (2017) also approached cross-country regressions in the hope of confirming their results from panel data, though this attempt proved insignificant. Our results contradict those of Kappel (2010), Beck et al (2007) and Clarke et al (2006) who used cross-sectional data as well. We believe that the differences in these results are due to inconsistencies between the income inequality databases (SWIID versus WIID), as highlighted by Jenkins (2015).

Turning to Column 3 which shows the interaction of financial development and the dummy for emerging markets. Even though FD coefficient did not change its effect, the interaction coefficient turns insignificantly-negative in almost all the models. Despite its insignificance and unreliability, the interaction coefficient shows that FD has a more narrowing-effect on inequality growth in EM compared to non-EM. For example, in the case of Credit-Gini D nexus, this effect can reduce half of the total widening-effect of Credit on Gini D growth.

Financial Efficiency and Income Inequality. Because our results seem to be mixed, we must be aware that these FD indicators behave differently. Higher levels of Net Interest Margin (Interest) show lower operating efficiency and competitiveness whereas higher levels of Stock Market Turnover Ratio (SMTR) indicate more efficiency. Since previous literature found benefits of higher efficiency of financial institutions on economic growth and inequality through improved resource allocation and high-return investments

(Demirguc-Kunt and Levine, 2009), we will focus our attention on the effect of enhanced bank efficiency on inequality.

On one hand, 1% increase in the Net Interest Margin would trigger an increase in the growth of the Gini D coefficient by 0.048 (Column1). Respectively, a decrease in the efficiency of the financial institutions and market imperfections would lead to an increase in income inequality. This translates in an inequality-widening effect of lower banks' efficiency, or equivalently in an inequality-narrowing effect of enhanced banks' efficiency. This is in line with findings of Zhang and Naceur (2019) and Casti (2018). On the other hand, this relationship does not hold for the Gini M since a unitary increase in Net Interest Margin (or in inefficiency) leads to a decrease in the growth of Gini M. This would support the inequality-narrowing hypothesis of lower banks' efficiency and respectively the inequality-widening hypothesis of enhanced banks' efficiency. This confirms our main hypothesis that FD widens inequality. Since the Net Interest Margin indicates banks' profitability and growth, a possible explanation for our results would be the fact that more profitable banks would become more greedier in selecting their customers, particularly looking for people with great capital amounts for investments.

TABLE 6. Effects of Financial Efficiency on Income Inequality.

Financial Efficiency	*GINI DISPOSABLE*			*GINI MARKET*		
	OLS (1)	*2SLS* (2)	*OLS Interaction* (3)	*OLS* (1)	*2SLS* (2)	*OLS Interaction* (3)
Interest	0.048*	-0.230	0.045*	-0.065**	-0.171***	-0.070**
Interest*EM			-0.009			-0.030
R-Squared	**0.611**	**0.026**	**0.611**	**0.391**	**0.290**	**0.404**
Observations	**72**	**72**	**72**	**77**	**77**	**77**
SMTR	0.002***	0.007*	0.003***	0.002**	0.008**	0.003**
SMTR*EM			-0.002*			-0.0003
R-Squared	**0.526**	**0.378**	**0.539**	**0.366**	**0.041**	**0.367**
Observations	**67**	**67**	**67**	**69**	**69**	**69**

In terms of Turnover Ratio, both Models (1) and (2) show a significantly-positive coefficient for SMTR, which translates as: the more efficient the financial markets, the higher the Gini growth and consequently the inequality. Similarly, Gimet and Lagoarde-Segot (2011) found that increased turnover ratios have a negative effect on inequality.

After controlling for endogeneity using the Protection of Property Rights index as an IV, the FD coefficients increased in size in all models and their signs are in line with our inequality-widening hypothesis of FD. Interestingly, the interaction between EM and SMTR proves to be significant and negative, meaning that in comparison with the other countries from the sample, EM experience a lower inequality-widening-effect of efficient stock markets, decreasing the growth of Gini D coefficient by -0.002% (Column3). In contrast, the other interaction coefficients are insignificant.

<u>Financial Stability and Income Inequality.</u> Both coefficients of Regulatory Capital to risk weighted assets ratio (RegCap) and Volatility of stock price index (Volatility) are significant. However, despite having the same sign, they have different effects on the growth of Gini. This is because high RegCap ratios trigger lower default risks for financial institutions (more stability) while high Volatility means more unstable financial markets.

TABLE 7. Effects of Financial Stability on Income Inequality

Financial Stability	*GINI DISPOSABLE*			*GINI MARKET*		
	OLS (1)	*2SLS (2)*	*OLS Interaction (3)*	*OLS (1)*	*2SLS (2)*	*OLS Interaction (3)*
RegCap	-0.046**	-0.142*	-0.046**	-0.037*	-0.093*	-0.040**
RegCap*EM			-0.002			-0.012
R-Squared	**0.612**	**0.458**	**0.613**	**0.454**	**0.359**	**0.487**
Observations	**55**	**55**	**55**	**55**	**55**	**55**
Volatility	-0.018*	-0.079*	-0.009	-0.017*	-0.088**	-0.013
Volatility*EM			-0.006			-0.003
R-Squared	**0.637**	**0.338**	**0.646**	**0.519**	**0.338**	**0.522**
Observations	**48**	**48**	**48**	**47**	**47**	**47**

Firstly, a 1% increase in RegCap would trigger a -0.046% decrease in the growth of Gini D coefficient (post-taxes income inequality), and respectively a -0.037% decrease in the growth of Gini M coefficient (pre-taxes income inequality). This finding on inequality-narrowing effect of the financial institutions' stability is in line with the results of Zhang and Naceur (2019) and Jeannyney and Kpodar (2011), who believe that financial instabilities and payment system disruptions are detrimental to the poor. A plausible explanation would be that banks which are in difficulty will start rationing small loans since poor borrowers are less profitable (*ibid*). Secondly, regarding the effect of financial markets' stability on income inequality, we notice that a 1% increase in Volatility (thus an increase in financial markets' instability) can result in a decrease of -0.018% in the Gini D growth, respectively -0.017% in Gini M growth. In other words, our results indicate that more stable financial markets would lead to greater levels of income inequalities, and this effect is slightly larger on post-taxes income inequality than on pre-taxes one. This finding on the inequality-widening effect of financial stability contradicts Zhang and Naceur (2019). The coefficients of RegCap and respectively Volatility do not change their sign, but they increase in size after controlling for endogeneity using the Legal Origin dummy, and respectively the Protection of Property Rights index as IV (Column2).

Column3 reports the results of our interaction of financial stability with EM. For instance, the RegCap-EM interaction coefficient (though insignificant) shows that the financial stability of the banking institutions (measured by RegCap) has a more-narrowing effect on income inequality in EM, compared to non-EM. This means that an EM will usually experience an additional decrease of 0.002 units in the growth of income inequality due to a 1% increase in the financial stability indicator. Contrasting results can be found though for the interaction between Volatility and EM. Now the interaction coefficient (which is also insignificant) shows that high financial instability (high Volatility) decreases the growth of Gini D coefficient by an additional -0.006 units to the initial -0.009 units, if the country is an EM. This finding comes as a surprise and in contradiction with most of the literature. Guillaumont-Jeanneney and Kpodar (2006) state that developing countries, with poor legal systems or macroeconomic policies, are more prone to financial instabilities which can arise together with the financial system development. However, for financial markets, high volatility can also translate into possibility of high returns.

Financial Access and Income inequality. As we can see from the small number of observations, data on financial access indicators is scant and has its own limitations, thus the reliability of our results might be questionable. Surprisingly, we face mixed results when comparing results for Gini D (based on post-taxes incomes) and Gini M (based on pre-taxes incomes). In the case of post-taxes income inequality, the coefficient of the Value (which stands for Value traded outside top 10 trading companies to the total trading value) is positive and significant (Column1). This confirms the inequality-widening effect of this financial access indicator. Contrary to this finding, in the case of pre-taxes income inequality, the Value coefficient is negative (though insignificant at 10% significance level), supporting the inequality-narrowing hypothesis (as also confirmed by Casti, 2018; Zhang and Naceur, 2019). According to Casti (2018), these differences in the FD effect on post- and pre-taxes income inequalities can be justified by the existence of redistribution policies, particularly in developed countries which do not apply excessive taxes on capital gains.

TABLE 8. Effects of Financial Access on Income Inequality.

Financial Access	*GINI DISPOSABLE* *OLS (1)*	*2SLS (2)*	*OLS Interaction (3)*	*GINI MARKET* *OLS (1)*	*2SLS (2)*	*OLS Interaction (3)*
Value	0.007*	0.011	0.010**	-0.002	-0.001	-0.001
Value*EM			-0.011**			-0.005
R-Squared	**0.648**	**0.630**	**0.740**	**0.624**	**0.612**	**0.655**
Observations	**30**	**30**	**30**	**30**	**30**	**30**

Curiously, the coefficient of the interaction between Value and EM is significant at 5% significance level and has a negative effect on the growth of the Gini coefficient based on disposable (post-taxes) income (Column3). This means that EM experience an additional decrease in income inequality by 0.011 units as compared to the other countries, which generally face an inequality-widening effect on inequality.

4. Conclusions and Discussions

Table 9 compiles the statistically-significant effects of FD dimensions on inequality (after and before taxes). Firstly, the depth dimension, measured by Credit and SMV, has a widening-impact on both net and gross income inequality (Gini Disposable and Gini Market). Therefore, we failed to reject our main null hypothesis, and thus we imply that high income households take more advantage of bank loans and stock market earnings.

TABLE 9. Summary of Financial Development Effects on Inequality.

Financial Development Dimension	*Variable*	*Gini Disposable (after-taxes)*	*Gini Market (before taxes)*
↑ DEPTH	↑ Credit	↑ 0.002%	↑ 0.003%
	↑ SMV	↑ 0.002%	↑ 0.001%
↑ EFFICIENCY	↓ Interest	↓ -0.048%	↑ 0.065%
	↑ SMTR	↑ 0.002% (↑ 0.001%)	↑ 0.002%
↑ STABILITY	↑ RegCap	↓ -0.046%	↓ -0.037%
	↓ Volatility	↑ 0.018%	↑ 0.017%
↑ ACCESS	↑ Value	↑ 0.007% (↓ 0.001%)	-

Note: ↑ and ↓ refer to a widening-effect and respectively a narrowing-effect on the Gini coefficient growth. Values in parenthesis show the effect of the FD-EM interaction on the main FD coefficient. For instance, in the case of SMTR, the interaction coefficient -0.002, while the SMTR coefficient is 0.003. Therefore, the effect of the interaction equals 0.003 – 0.002 = 0.001. We only report the significant interaction coefficients. All coefficients are significant at 10% significance level. Caution must be taken when interpreting the Interest and Volatility indicators since, in comparison with the others, they have a mirrored-effect.

A more efficient financial system would mean decreasing the banks' Net interest margin and boosting the stock market's turnover ratio. Our dimension presents mixed results: the financial markets' efficiency (SMTR) triggers an increase in income inequality, whereas banks' efficiency (Interest) can reduce the disposable income inequality growth by -0.046%, but usually increases market income inequality growth by 0.065%. Interestingly, stock market efficiency has an equal impact on both net and gross income inequality growth, possibly explained by not stringent enough fiscal policies, lack of corporate taxes.

Similarly, an increase in the stability of financial system implies an increase in the RegCap ratio and a decrease in Volatility of the stock price index. Therefore, our results show that higher banks' stability pulls down inequality, this being the only indicator that confirms the inequality-narrowing hypothesis of FD. Conversely, higher stability in the stock market can generate a faster growth of disposable and market income inequality, losses hurting poor investors more than the rich ones, especially during crisis. Lastly, more access to the financial markets can trigger a faster growth rate of the net income inequality.

These have been said, most of our financial development indicators have an undesired positive effect on the growth of the Gini coefficients, meaning that we failed to reject our null hypothesis of the inequality-widening effect of financial development. As many other studies, we also confirm that the banking system has a greater impact than the stock market. In what regards the situation of EM, most of our interaction coefficients were insignificant, but all of them turned negative. This fails to reject our second null hypothesis that financial development has a more narrowing-effect on Income Inequality in EM. For instance, in Table 9, where we only report the significant results, the general inequality-widening effect of SMTR is attenuated by -0.002%. Hence, in an EM, the inequality widening-effect of SMTR decreases from 0.002% to 0.001%. Lastly, based on our results, EM with higher access to stock markets depict decreasing levels of inequality.

Our findings add to a significant policy-oriented literature on the finance-inequality nexus across countries, and especially in EM. Firstly, we must admit there is no general approach to deal with inequality, as countries differ greatly in terms of inequality drivers, policy-making and institutional frameworks. However, Dabla-Norris *et al* (2015) recommends DM to concentrate their policies on a more progressive tax system or higher corporate taxes, and increasing human capital and skills. In EM, policy-makers should ensure that larger financial systems go along with greater access. But it should also be better regulated and supervised in order to achieve efficiency and avoid imbalances and over-investment in real estate. Policies targeting the banking system's stability should be encouraged and default risks avoided. Last but not least, we believe that greater financial inclusion in EM promotes lower inequalities among people, as well as more investments.

Before concluding, we must discuss the limitations of our analysis. Firstly, cross-country comparative analysis of income inequality is usually plagued with problems of unreliability, inconsistent methodology or limited coverage (Jaumotte *et al*, 2013). Atkinson and Brandolini (2001) claim that this kind of problems may arise when using secondary datasets instead of original data. We believe that in our analysis we might face such problems. Moreover, data on some FD indicators is quite limited. For instance, the access dimension should be updated so that researchers can take full advantage of its significance in analysing the financial exclusion phenomenon (Honohon, 2008). Unfortunately, the access dimension of the banking system could not be considered in our paper. Secondly, from an econometric point of view, cross-country regressions suffer from a number of pitfalls which might restrict our analysis. Since they do not take into account the time-series aspect of the data and do not exercise a thorough control for unobserved entity-specific effects (Beck *et al*, 2007), a dynamic panel-data analysis, using either fixed or random effects, would be more appropriate.

Lastly, theory is still unclear whether FD has a narrowing- or widening-effect on inequality. Our findings mainly support the inequality-widening hypothesis, in line with deHaan and-Sturm (2017), Jauch and Watzka (2016), Denk and Cournede (2015), Jaumotte *et al* (2013), Gimet and Lagoarde-Segot (2011). However, it is essential to stress out that our findings do not necessarily imply that FD is bad for poor people since we do not focus on the income of a specific quintile of the population. Thus, I would like to emphasize that this widening phenomenon of inequality should not be treated as a *"normal"* negative externality of a more developed financial system. It is true that financial development can uplift the *"small boats"*, at least up to a threshold, but we should also be aware of its harmful impact.

Bibliography

Abiad, A., Detragiache, E. and Tressel, T. (2010). A new database of financial reforms. *IMF Institute of Research Department Working Paper*, 57, pp. 281–302.

Abiad, A., Oomes N. and Ueda, K. (2008). The quality effect: does financial liberalization improve the allocation of capital? *Journal of Development Economics*, 87, pp. 270–282.

Afonso, H., LaFleur, M. and Alarcon, D. (2015). Inequality Measurement. Development Issues No. 2. *Development Policy and Analysis Division of UN/DESA*.

Aghion, P. and Bolton, P. (1997). A theory of trickle-down growth and development. *Review of Economic Studies*, 64, pp. 151–172.

Alesina, A., Devleeschauwer, A., Easterly, W., Kurlat, S. and Wacziarg, R. (2003). Fractionalization. *Journal of Economic Growth*, 8(2), pp.155–194.

Allen, F (2012). Trends in financial innovation and their welfare impact: An overview. *European Financial Management,* 18(4), pp: 493–514.

Atkinson, A.B. (1975). *The Economics of Inequality*. Oxford: Clarendon Press.

Atkinson, A.B. (2015). *Inequality: What can be done?* Cambridge, MA: Harvard University Press.

Atkinson, A.B. and Bourguignon, F. (2015). *Handbook of Income Distribution*. Volume 2. 1st Ed. North-Holland: Elsevier.

Atkinson, A.B. and Brandolini, A. (2000). *Promise and Pitfalls in the Use of 'Secondary' Data-Sets: Income Inequality in OECD Countries.* Temi di discussione (Economic working papers) 379, Bank of Italy, Economic Research and International Relations Area.

Bakija, J., Cole, A., and Heim, B. T. (2012). *Jobs and income growth of top earners and the causes of changing in income inequality: Evidence from US tax return data*. Unpublished manuscript, Williams College.

Banerjee, A.V. and A.F. Newman. (1993). Occupational choice and the process of development. *Journal of Political Economy,* 101, pp. 274–98.

Barro, R.J. and Jong-Wha, J. W. (1996). International measures of schooling years and schooling quality. *AER Papers and Proceedings*, 86, pp. 218–223.

Barro, R.J. and McCleary, R.M. (2003). *American Sociological Review*, 68(5), pp. 760-781.

Beck, T., Demirguc-Kunt, A. and Levine, R. (2003). Law and Finance: Why does Legal Origin Matter? *Journal of Comparative Economics*, 31(4), pp. 653-675.

Beck, T., Demirgüç-Kunt, A. and Levine, R. (2007). Finance, inequality and the poor. *Journal of Economic Growth*, 12, pp. 27-49.

Beck, T., Levine, R. and Loayza, N. (2000). Finance and the sources of growth. *Journal of Financial Economics*, 58, pp.261-300.

Belley, P. and Lochner, L. (2007). The Changing Role of Family Income and Ability in Determining Educational Achievement. *Journal of Human Capital*, 1(1), pp. 37-89.

Bellu, L.G. and Liberati, P. (2006a). Policy Impacts on Inequality: Welfare Based Measures of Inequality – The Atkinson Index. *Food and Agriculture Organization of the United Nations.*

Bellu, L.G. and Liberati, P. (2006b). Policy Impacts on Inequality. Inequality and Axioms for its Measurement. *Food and Agriculture Organization of the United Nations.*

Bergh, A. (2005). On the counterfactual problem of welfare state research: how can we measure redistribution? *European Sociological Review*, 21(4), pp. 345–357.

Besley, T. and Ghatak, M. (2010). Property Rights and Economic Development. Chapter 68. *Handbook of Development Economics*, pp. 4525-595.

Bolton, P., Santos, T. and Scheinkman, J.A. (2016). Cream-Skimming in Financial Markets. *The Journal of Finance*, 71, pp. 709-736.

Brei, M., Ferri, G. and Gambacorta, L. (2019). . VOX CEPR Policy Portal. Available at: https://voxeu.org/article/how-finance-affects-income-inequality (Accessed: 12th August 2019).

BSE – Budapest Stock Exchange. (2019). Composition of the BUX Basket. Available at: https://bse.hu/pages/index-baskets#BUX (Accessed: 2nd September 2019).

Bulir, A. (2001). Income inequality: does inflation matter? *IMF Staff Papers*, 48(1), pp. 139-159.

Bumann, S. and Lensink, R. (2016). Capital account liberalization and income inequality. J. Int. Money Financ. 61, pp. 143–162.

Burgess, R, Pande, R (2005). Can rural banks reduce poverty? Evidence from the Indian social banking experiment. *American Economic Review*, 953(3), pp. 1-35.

Campano, F. and Salvatore, D. (2006). *Income Distribution*. Oxford: Oxford University Press.

Casti, C. (2018). Income Inequality and Financial Development: A Multidimensional Approach. 35th IARIW General Conference, August 20-25, Copenhagen.

Cihak, M., Demirguc-Kunt, A., Feyen, E. and Levine, R. (2012). Benchmarking Financial SystEM around the World. *Policy Research Working Paper* 6175.

Clarke, G., Xu, L. C., and Zou, H. (2006). Finance and income inequality: What do the data tell us? *Southern Economic Journal*, 72, pp. 578–596.

Cobham, A. and Sumner, A. (2013). Putting the Gini Back in the Bottle? The Palma as a Policy-Relevant Measure of Inequality. London: King's College London.

Cobham, A., Schlogl, L. and Sumner, A. (2016). Inequality and the Tails: the Palma Proposition and Ratio. *Global Policy*, 7(1), pp. 25-36.

Cowel, F.A. and Flachaire, E. (2018). Inequality Measurement and the Rich: Why inequality increased more than we thought. *STICERD - Public Economics Programme Discussion Papers,* 36, Suntory and Toyota International Centres for Economics and Related Disciplines, LSE.

Cowell, F. (2016). Inequality and Poverty Measures. In Adler, M.D., Fleurbaey, M. and Cowell, F. (ed.) *The Oxford Handbook of Well-Being and Public Policy*. Oxford University Press.

D'Agostino, R.B., Belanger, A.J. and d'Agostino Jr., R.B. (1990). A suggestion for using powerful and informative test of normality. *American Statistician*, 44, pp. 316-321.

Dabla-Norris, E., Kochhar, K., Suphaphiphat, N., Ricka, F. and Tsounta, E. (2015). Causes and Consequences of Income Inequality: A Global Perspective. *International Monetary Fund.*

De Haan, J. and Sturm, J.E. (2017). Finance and income inequality: A review and new evidence. *European Journal of Political Economy*, 50, pp. 171–195.

De Haan, J., Pleninger, R. and Sturm, J.E. (2018). Does the impact of financial liberalization on income inequality depend on financial development? Some new evidence. *Applied Economics Letters*, 25(5), pp. 313-316.

De Soto, H. (2000). *The Mystery of Capital: Why Capitalism Triumphs in the West and Fails Everywhere Else*. New York: Basic Books.

Deininger, K., and Squire, L. (1996). A new data set measuring income inequality. *The World Bank Economic Review*, 10(3), pp. 565-591.

Delis, M. D., Hasan, I., and Kazakis, P. (2013). Bank regulations and income inequality: Empirical evidence. *Review of Finance*, 18(5), pp. 1811-1846.

Delis, M.D., Hasan, I. and Kazakis, P. (2014). Bank regulations and income inequality: empirical evidence. *Review of Finance*, 18, pp. 1811–1846.

DeMaio, F. (2007). GLOSSARY: Income inequality measures. *Journal of Epidemiology and Community Health*, 61(10), pp. 849-852.

Demirguc-Kunt and Levine, R. (2009). Finance and Inequality: Theory and Evidence. *Annual Review of Financial Economics*, 1, pp. 287-318.

Demirgüç-Kunt, A and Levine, R. (2001). *Financial structures and economic growth: a cross-country comparison of banks, markets, and development*. Cambridge: MIT Press.

Denk, O. and Cazenave-Lacroutz, A. (2015). Household finance and income inequality in the euro area. *OECD Economic Department Working Papers*, 1266.

Diamond, P. A. (2016). Addressing the forces driving inequality in the United States. *Contemporary Economic Policy*, 34(3), pp. 403-411.

Djankov, S., LaPorta, R., Lopez-de-Silanes, F., Shleifer, A. (2003). Courts. *Quarterly Journal of Economics,* CXVIII, pp. 453–517.

Dollar, D. and Kraay, A. (2002). Growth Is Good for the Poor. *Journal of Economic Growth*, 7, pp. 195-225.

Easterly, W. and Fischer, S. (2001). Inflation and the poor. *Journal of Money, Credit and Banking*, 33(2), pp. 160-178.

Economic Freedom Dataset (2018). *The Fraser Institute*. Available at: https://www.fraserinstitute.org/economic-freedom/dataset?geozone=world&page=dataset&min-year=2&maxyear=0&filter=0 (Accessed: 23rd July 2019).

ESRB European Systemic Risk Board (2014). Is Europe Overbanked? *Reports of the Advisory Scientific Committee 4*, European Systemic Risk Board.

Fernández, A., and Tamayo, C. E. (2017). From Institutions to Financial Development and Growth: What are the Links? *Journal of Economic Surveys*, 31(1), pp. 17-57.

Florida, R. (2014). *The Link between Religious Diversity and Economic Development*. CityLab. Available at: https://www.citylab.com/equity/2014/12/the-link-between-religiousdiversityand-economic-development/372585/ (Accessed: 30th August 2019).

Galbraith, J. K. (2009). Inequality, unemployment and growth: New measures for old controversies. *Journal of Economic Inequality*, 7(2), pp. 189-206.

Galor, O., and Moav, O. (2004). From physical to human capital accumulation: Inequality and the process of development. *Review of Economic Studies*, 71, pp. 1001–1026.

Galor, O., and Zeira, J. (1993). Income distribution and macroeconomics. *Review of Economic Studies*, 60, pp. 35–52.

Gimet, C. and Lagoarde-Segot, T. (2011). A closer look at financial development and income distribution. *Journal of Banking and Finance*. 35, pp. 1698-1713.

Green, G.W. Jr., Coder, J. and Ryscavage, P. (1994). Earnings Inequality for Men in the 1980s. in *Aspects of Distribution of Wealth and Income*. Ed. Papadimitriou Dimitris. London: Macmillan.

Greenwood, J. and Jovanovic, B. (1990). Financial development, growth, and the distribution of income. *Journal of Political Economy*, 98, pp. 1076–1107.

Greenwood, R. and Scharfstein, D. (2013). The growth of modern finance. *Journal of Economic Perspectives,* 27(2), pp.: 3–28.

Guillaumont Jeanneney, S. and Kpodar, K. (2006). Développement financier, instabilité financière et croissance économique. *Economie et Prévision*, 174(3), pp. 87–111.

Haas, R. (2004). Law, finance, and growth during transition: a survey. *De Economist,* Springer, 152(3), pp. 375–402.

Hamori, S. and Hashiguchi, Y. (2012). The effect of financial deepening on inequality: Some international evidence*. Journal of Asian Economics*, 23(4), pp.353–359.

Hao, L. and Naiman, D.Q. (2011). *Quantitative Applications in the Social Sciences: Assessing Inequality*. SAGE Publications, Inc.

Harrison, A., McLaren, J. and McMillan, M. (2011). Recent Perspectives on Trade and Inequality. *The Annual Review of Economics*, 3, pp. 261-289.

Hasell, J. (2018). Is income inequality rising around the world? OWID. Available at: https://ourworldindata.org/income-inequality-since-1990#note-4 (Accessed: 21st August 2019).

Haughton, J. and Khandker, S.R. (2009). *Handbook on poverty and inequality*. The World Bank: Washington, DC.

Honohon, P. (2008). Cross-country variation in household access to financial services. *Journal of Banking and Finance*, 32(11), pp. 2493-2500.

Huggett, M., Ventura, G., and Yaron, A. (2011). Sources of lifetime inequality. *The American Economic Review*, 101(7), pp. 2923-2954.

Jauch, S. and Watzka, S. (2016). Financial Development and Income Inequality: A Panel Data Approach. *Empirical Economics*, 51(1), pp. 291–314.

Jaumotte, F., Lall, S., and Papageorgiou, C. (2013). Rising income inequality: technology or trade and financial globalization? *IMF Economic Review*, 61(2), pp. 271-309.

Jaumotte, F., Papageorgiou, C. and Lall, S. (2013). Rising Income Inequality: Technology, or Trade and Financial Globalization? *IMF Economic Review*, 61(2), pp. 271–309.

Jeanneau, S. (2007). *Banking systems: characteristics and structural changes*, BIS Papers, 33, pp. 3-16.

Jeanneney, S.G. and Kpodar, K. (2011). Financial Development and poverty reduction: Can there be a benefit without a cost? *Journal of Development Studies*, 47(1), pp. 143-163.
Jenkins, S.J. (2015). World income inequality databases: an assessment of WIID and SWIID. *The Journal of Economic Inequality*, 13, pp. 629-671.
Kaplan, S. N. and Rauh, J. (2010). Wall Street and Main Street: What contributes to the rise in the highest incomes? *Review of Financial Studies*, 23(3), pp. 1004-1050.
Kawachi, I. (2000). Income Inequality, In *Social Environment Notebook*. Available at: https://macses.ucsf.edu/research/socialenviron/inequality.php (Accessed: 23rd August 2019).
Kim, D.H. and Lin, S.C. (2011). Nonlinearity in the financial development-income inequality nexus. *Journal of Comparative Economics*, 39, pp. 310-325.
King, R. and Levine, R. (1993). Finance and growth: Schumpeter might be right. *Quarterly Journal of Economics*, 108, pp. 717-738.
Klasen, S., Scholl, N., Lahoti, R., Ochmann, S. and Vollmer, S. (2016). Inequality - worldwide trends and current debates, Discussion Paper No. 209, *Courant Research Centre: Poverty, Equity and Growth*, University of Göttingen.
Krozer, A. (2015). The Inequality We Want: How Much is too Much? WIDER Working Paper 2015. *World Institute for Development Economics Research*.
Kum, H. (2008), *Inequality and its relationship with structural change*, UNRISD Working paper.
Kunieda, T., Okada, K. and Shibata, A. (2014). Finance and inequality: How does globalization change their relationship*? Macroeconomic Dynamics*, 18(5), pp.1091-1128.
Kuznets, S. (1955). Economic growth and income inequality. *American Economic Review*, 45(1), pp. 1-28.
LaPorta, R., Lopez-de-Silanes, F., Shleifer, A. and Vishny, R. (1998). Law and Finance. Journal of Political Economy, 106, pp. 1113-1155.
LaPorta, R., Lopez-de-Silanes, F., Shleifer, A. and Vishny, R. (1997). Legal determinants of external finance. *Journal of Finance*. 2, pp. 1131–1150.
Law, S.H and Azman-Saini, W.N.W (2012). Institutional quality, governance and financial development. *Econ. Gov*., 13, pp. 217-236.
Law, S.H., Tan, H.B. Azman-Saini, W.N.W. (2014). Financial development and income inequality at different levels of institutional quality. *Emerging Markets Finance and Trade* 50, pp. 21–33.
Le Roux, M. (2013). ‘It’s plain sailing for one manufacturing industry’, *The Times,* London, 25th September.
Levine, R., Loayza, N. and Beck, T. (2000). Financial intermediation and growth: Causality and causes. *Journal of Monetary Economics*, 46, pp. 31-77.
Li, H., Squire, L. and Zou, H. (1998). Explaining international and intertemporal variations in income distribution. *The Economic Journal*, 108, pp. 26-43.
Lindert, P.H. and Willimson, J.G. (1985). Growth, Equality and History. *Explorations in Economic History*, 22, pp. 341-377.
OECD Report (2016). *Income inequality update. Income inequality remains high in the face of weak recovery.* Available at: https://www.oecd.org/social/OECD2016-Income-InequalityUpdate.pdf (Accessed: 2nd June 2019).
Ortiz, I. and Cummins, M. (2011). Global Inequality: Beyond the Bottom Billion – A Rapid Review of Income Distribution in 141 Countries. Available at SSRN: https://ssrn.com/abstract=1805046 or http://dx.doi.org/10.2139/ssrn.1805046 (Accessed: 1st September 2019).
Oxley, H., Burniaux, J.-M., Dang, T.-T. and d’Ercole, M. (1997). Income Distribution and Poverty in 13 OECD Countries. *OECD Economic Studies*, 29(2).
Paukert, F. (1973). Income Distribution at Different Levels of Development: A Survey of Evidence. *International Labor Review*, 108, pp. 97-125.
Perkins, D.H., Radelet, S., Lindauer, L. and Block, S.A. (2013). *Economics of Development*. 7th Ed. W.W. Norton & Company: New York, N.Y.; London.
Piketty, T (2014). *Capital in the Twenty-First Century*, Cambridge: Belknap Press.
Rajan, R. G. and Zingales, L. (2014). *Saving capitalism from the capitalists*. New York: Crown Business.
Rajan, R.G. (2010). Rebalancing the Global Economy. *New Perspectives Quarterly,* 27(4), pp.: 7-9.

Rajan, R.G. and Zingales, L. (2003). The great reversals: the politics of financial development in the twentieth century. *Journal Financial Economics*, 69, pp. 5–50.
Roser, M. and Ortiz-Ospina, E. (2016). Income Inequality. Our World in Data. Available at: https://ourworldindata.org/income-inequality#note-8 (Accessed: 31st August 2019).
Sacerdoti, E. (2005). Access to Bank Credit in Sub-Saharan Africa: Key Issues and Reform Strategies. *IMF Working Paper*, 5(166).
Seven, U and Coskun, Y (2016). Does financial development reduce income inequality and poverty? Evidence from emerging countries. Emerging Markets Review, 26, pp. 34-63.
Solt, F. (2008). Standardizing the world income inequality database. Social Science Quarterly, 90, pp. 231-242.
Solt, F. (2015). On the assessment and use of cross-national income inequality datasets. *The Journal of Economic Inequality*, 13, pp. 683-691.
Solt, F., (2019), *The Standardized World Income Inequality Database*, Version 8, Available at: https://doi.org/10.7910/DVN/LM4OWF, Harvard Dataverse, V2.
Stock, J.H. and Watson, M.W. (2015). *Introduction to Econometrics*. 3rd Ed., Pearson International Edition.
Summers, R., Kravis, I.B. and Heston, A. (1984). Changes in the World Income Distribution. *Journal of Policy Modelling*, 6(2), pp. 237-269.
Tan, H. B., and Law, S. H. (2012). Nonlinear dynamics of the finance-inequality nexus in developing countries. *The Journal of Economic Inequality*, 10(4), pp. 551-563.
University of Texas Inequality Project. (2013). The UTIP-UNIDO Data Set. Available at: http://utip.gov.utexas.edu/data.html.
Williamson, R. and Stulz, R.M. (2001). Culture, Openness and Finance. NBER Working Paper No. w8222. Available at SSRN: https://ssrn.com/abstract=266192 (Accessed: 12th August 2019).
Wooldridge, J.M. (2013). *Introductory Econometrics: A Modern Approach*. 5th Ed., South Western.
World Bank (2005). *Introduction to Poverty Analysis*. Washington, DC: World Bank Group.
Yunus, M. and Weber, K. (2017). *A world of three zeros: The new economics of zero poverty, zero unemployment and zero net carbon emissions*. 1st Ed. New York: Public Affairs.
Zhang, R. and Naceur, S.B. (2019). Financial Development, Inequality and Poverty: Some International Evidence. *International Review of Economics and Finance*, 61, pp. 1-16.

Additional Sources

Note: These tables should not be included in the essay. They are only given in order to facilitate the reader's understanding. For additional information regarding the composition of the dataset or any calculations, please contact the author.

TABLE A. Instrumental Variables Used in the Regressions

Instrumental Variable	*Description*	*Source*
Legal Origin	Dummy variable with values 1 (British Common Law origin) and 0 (otherwise)	LaPorta *et al* (1998)
Protection of Property Rights	Averaged values (1995, 2000-2014) (The higher its values, the more protection.)	Economic Freedom Dataset (2018)
Religious Fractionalization	Values for 2001 (only ones available) (The higher its values, the more religiously fractionized the society is.)	Alesina *et al* (2003)

TABLE B. Control Variables Used in the Regressions

*Control Variables - Sources: World Bank World Development Indicators Database; Barro and Lee (1996)***		
Variable	***Description***	***Rationale***
GDP per Capita Growth	Annual percentage change of GDP per capita growth	Controls the level of economic growth. It is believed there is a strong relationship between economic development and income distribution (Zhang and Naceur, 2019).
Population Growth	Average annual growth rate of the total population	Controls for demographic factors.
Inflation	The growth rate of the GDP deflator	Controls for the macroeconomic stability (Beck *et al*, 2007). It may affect nominal wages, and it is related to the labour union strength. In the event of hyperinflation, the real value of cash decreases and the wealthy people (who own other assets than cash) are better off than the poor. Hence, reductions in inflation lowers income inequality (Bulir, 2001).
Government Consumption to GDP	All current governmental expenses for purchasing goods/services (including employees' compensation, national security/defence expenses, but not expenses related to government capital formation).	Captures the public spending and the provision of public goods. If efficiently allocated, through redistributive policies that help the poor, public spending could have a positive impact (Casti, 2017).
Trade Openness to GDP	Sum of exports and imports of goods and services measured as a share of gross domestic product.	Captures the international exposure and openness to foreign trade (Beck *et al*, 2007). Based on the Heckscher-Ohlim theorem, differences between countries can be explained by productivity and factors of production. On one hand, advanced countries which abound in skilled labour should experience an increase in their skilled workers' wages relative to the unskilled ones. On the other hand, developing countries, in which unskilled labour is more evident, should experience the opposite effect, meaning a declining inequality with trade (Harrison, McLaren and McMillan, 2011).
Initial Schooling**	Logarithm of the initial average years of school attainment	Proxy for human capital (Beck *et al,* 2007). Depending on the free access or not to the educational system, school attainment may affect inequality considerably (Huggett, Ventura and Yaron, 2011). High supply of human capital diminishes the wage differences between skilled and unskilled workers, and brings more technological innovations (Kim and Lin, 2011).
Initial Gini	Logarithm of the initial Gini coefficient (the value of the first year from the sample panel dataset)	Controls for the convergence effect, namely that poorer economies' initial Gini will decrease at a faster rate than the richer ones.
Age Dependency Ratio	Ratio of dependents (people younger than 15 or older than 64) to the working-age population (those ages 15-64).	Expresses the financial pressure exercised on the productive segment of the population.

Note: All variables are averaged for the period 1995-2014, except for the Initial Schooling and Initial Gini. All variables enter the regressions in natural logarithmic form, except for Inflation, GDP per capita Growth, Population Growth.

TABLE C. Countries Used in the Regressions

Emerging Markets	*Developed Markets*	*Frontier Markets*	*Unclassified Countries*
Argentina	Australia	Bangladesh	Armenia
Brazil	Austria	Botswana	Costa Rica
Chile	Belgium	Croatia	Cote d'Ivoire
China	Canada	Estonia	Cyprus
Colombia	Denmark	Jamaica	Ecuador
Czech Republic	Finland	Jordan	Ghana
Egypt	France	Kazakhstan	Guatemala
Greece	Germany	Kenya	Honduras
Hungary	Hong Kong	Lithuania	Iran
Indonesia	Ireland	Morocco	Korea
Malaysia	Israel	Panama	Kyrgyztan
Mexico	Italy	Romania	Latvia
Pakistan	Japan	Slovenia	Luxembourg
Peru	Netherlands	Sri Lanka	Malawi
Philippines	New Zealand	Tunisia	Mauritania
Poland	Norway		Moldova
Russia	Portugal		Rwanda
South Africa	Singapore		Slovakia
Thailand	Spain		Tajikistan
Turkey	Sweden		Tanzania
	Switzerland		Tonga
	United Kingdom		Uruguay
	United States		Venezuela

Examining the relationship between FDI and economic growth in context of COVID-19 pandemic: an empirical investigation of Romania's economy[1]

Negulescu Raluca Elena

Bucharest University of Economic Studies

Master of Science in Corporate Finance

Abstract

The purpose of this research paper was to study what impact can have the level of FDI inflows on the economic growth and also to investigate if this influence was affected by the COVID-19 crisis. The study indicates that the economies which are engaged in attracting foreign capital from other developed countries want to increase their economy and this thing is constructive even if are opinions which consider that the local market can be affected. It can be stated that with the support of foreign companies which allocate their capital in developing countries also called host countries, the development to other directions is also supported such as: implementing new technologies, improving foreign trade or adjusting some new legislative orders. Regarding to the coronavirus crisis there is a problem because the study indicates that in the current situation the level of FDI inflows is decreasing and this will affect the economic growth in a negative manner. Thus, the research aims to demonstrate the shocks suffered by the Romanian economy following the decrease in the level of FDI inflows due to the COVID-19 pandemic and the impact of this diminution on its economic growth.

Key words: FDI, GDP, COVID-19, Romania, economic growth

[1] This paper contains 19 pages, excluding first page and bibliography, but including the Appendix.

1. Introduction

In the last years developing countries have become an attraction for foreign investors because, in line with globalization, the trade partnerships between states have also developed. On the other hand, an economy without investments will be at a loss and for this reason the allocated resources will be limited following the prioritization of national interests. Thus, the foreign direct investments should be encouraged by the system as a long-term source of financing and development, because they are not only an inflow of capital, but are a stability source for an economy.

When we talk about foreign direct investments, we should think about an investment made by a non-resident company in the business of another country and which usually involves managerial imposition on the company in which the investor has invested. Following the process, the foreign investors will gain managerial power and will be able to impose their own ideas to increase the company’s productivity.

This is the case of Romania which has known an upward trend of FDI inflows in the last years. Many investors usually choose an open economy that offers skilled workforce to place their capital to ensure a high level of the labor productivity within the company. It can be stated as a key feature of FDI is to influence the decision-making process of a foreign business.

But the problem arises in extreme cases of crisis because the level of the FDI inflows will decrease and this will only lead to a shock in the national economy. Currently, the crisis which affects the entire globe is the COVID-19 pandemic. In Romania the current socio-economic context is dominated by the medical crisis, with an impact on the income and health of the population. This virus led to a national crisis which has reduced revenues and maximized the budgetary expenses, so the Romanian system is prone to a high level of financial stress. Thus, viable measures must be taken to ensure the safety and health of the population.

Do this fact, this paper aims to investigate whether the level of the FDI inflows has an influence on the economic growth in Romania and what shocks will suffer the economy during a crisis such as the COVID-19 pandemic. The study is divided into four sections followed by the conclusions. In the first one is presented an introduction to the proposed topic, then the second section will offer information from other studies about the subject and will summaries the theoretical framework of the paper. Further, the third section will illustrate the methodology and data used, following that later, the fourth section will present the empirical results generated by the model.

2. Theoretical framework

Over time, it has been examined in many research papers the subject regarding the determinants of FDI and their influence on economic growth. In many studies was found a positive relationship between these two variables, such as de Mello (1997), Carbonell and Werner (2018), Carkovic and Levine (2002). The last ones said in their study that FDI inflows contribute to an increase of economy through different forms. One of them could be the capital accumulation by the inputs into the production process. Also, FDI means a very important source of technology for developing and improvement of human capital.

The researchers Iqbal et al. (2010) have studied the relationship between FDI, trade and economic growth in Pakistan for the period 1998-2009. They used quarterly data series and following the application of the model, they found a long-run relationship and bidirectional causality among foreign direct investments, economic growth and export and, on the other hand, a unidirectional causality between import, export and FDI. Following these results, they concluded that FDI inflows affect the level of GDP and also the export and import have an influence by its level. Other studies like Suliman et al. (2018), Duarte et al. (2017), Akoto (2016) have indicated a significant impact on the GDP level by FDI inflows in the economy.

But the true challenge for an economy appears in cases of crisis. This is what happened with the Romanian economy in the last months. A certain fact following the coronavirus pandemic is the decrease in the level of FDI inflows which will lead to a reduction in GDP, based on the direct relationship between the variables. Due to this fact, the European countries have been warned by the European Commission about foreign direct investments and the capital flows, because the spread of coronavirus will impact the earnings of the companies and a recover will be very difficult to them.

3. Methodology and data

In this section will discuss the model approach characteristics. Thus, the methodology will describe the technical characteristics of the used model.

3.1 Model specification

Vector autoregression (VAR) is a statistical model used by economists into their studies for examining the relationship between multiple variables as they change during the time. The VAR models are an accumulation of the autoregressive models (AR), based on the concept of interdependencies of the lagged values of the variables in a model. This type of model is very used as a tool of investigation the dynamic effects of shocks also for forecasting the exercises.

A VAR model of order *p*, also called as VAR(*p*) model, can be written as:

$$y_t = \alpha_0 + \beta_1 y_{t-1} + \cdots + \beta_p y_{t-p} + \varepsilon_t \ ,$$

where: y_t is an $M \times 1$ vector of endogenous variables, α_0 is an $M \times 1$ intercept vector, β_j $(j = 1, \dots, p)$ are $M \times M$ coefficient matrices and ε_t is an $M \times 1$ vector of error terms, independently identically and normally distributed (*i.i.d*).

The researchers Ciccarelli and Rebucci (2003) indicated in their study that the model mentioned above, when estimated through the standard approach, it is getting to the “over-fitting” problem. This is generated by the fact that the numbers of coefficients to be estimated is $M + M^2 p$, increasing geometrically by the numbers of included variables and linearly by the lags order.

Based on the economic theory, we consider that a VAR estimation is better than a simple or a general linear statistical model because its endogenous and exogenous variables are in collaboration as part of the economic system. Accordingly, a VAR model is looking to be more accurate for the economic reality. As advantages of the model we can list some mentioned by Vorbeek (2004) in his research paper such as the more accurate forecasting which is possible because the information set is extended to also include the history of the other variables. Another advantage could be that the model may be thriftier, and it includes even less lags.

The correlation between VAR and structural simultaneous equations shows an advantage for VAR due to the characteristics of the variables which does not have to be a priori, this is what Sims (1980) said in his study. Furthermore, the theory confirms that OLS is a good estimator for the model because the variables are identical on the two sides of equalities.

Despite of all the good words about VAR, the model is not without critics. In this case, it is demonstrated that the model does not offer details about the determination of the results of the economic process. Also, it is investigated by some economists that is hard to observe some circumstances so that the model does not register errors (Darnel & Evans, 1990).

Another weakness of the VAR approach could be the large number of estimated parameters with many lags which will lead to risk model with fewer degrees of freedom (Rubinfeld, 1997). Harvey (1990) mentioned another problem of the VAR approach which is the stationarity because there are some circumstances when certain risks are significant and results from some mediocre data.

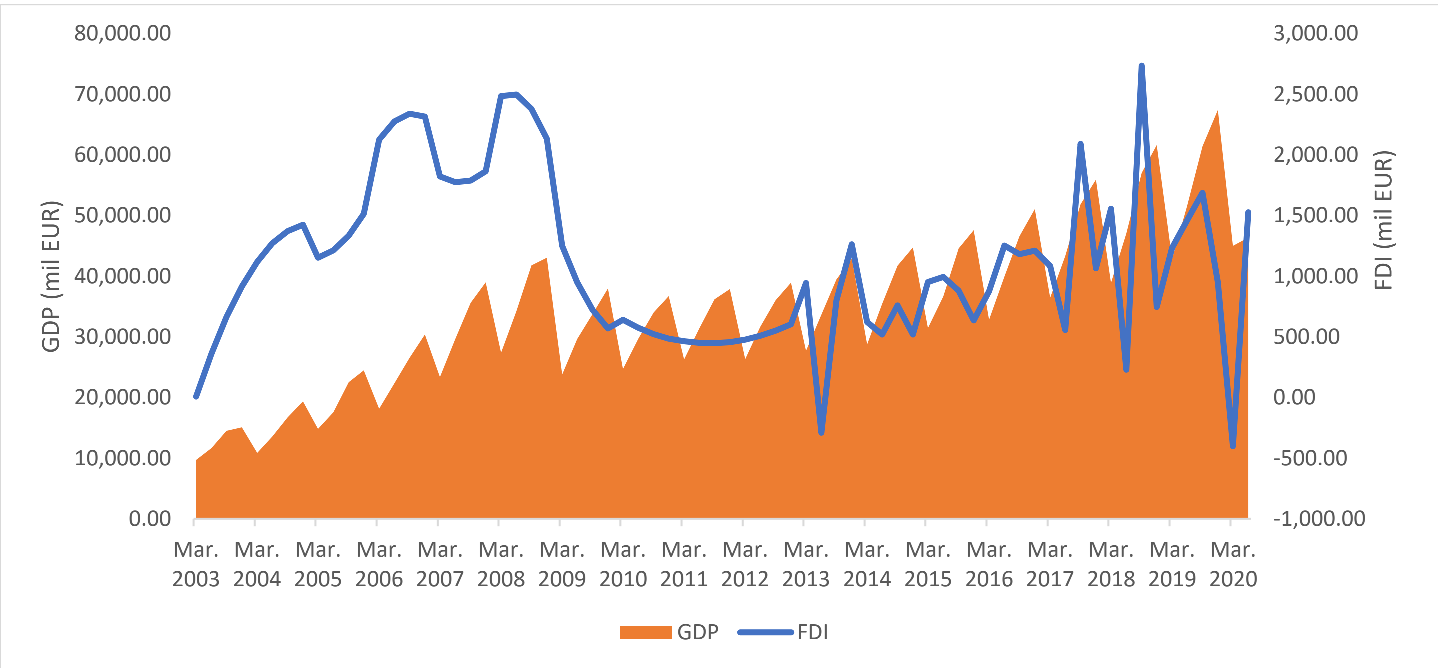
3.2 Data source

The topic of this paper is to determine the relationship between FDI and economic growth in Romania, during the period 2003Q1 – 2020Q2, using quarterly data such as the unemployment rate, harmonized index of consumer prices, export, import and ROBOR 3M kindly provided by Eurostat, NBR database and INSSE. Moreover, to investigate what impact had the COVID-19 pandemic to these variables and to compute a VAR(p) model in order to provide a better perspective about the variables.

4. Empirical analysis

In this chapter we will provide the results generated by the used model to determine what impact had the inflows of FDI to the economic growth. As we can see in Figure 1, both FDI and GDP followed an upward trend during the related period. Thus, we can confirm the economic theory which claims the direct relationship between these two variables.

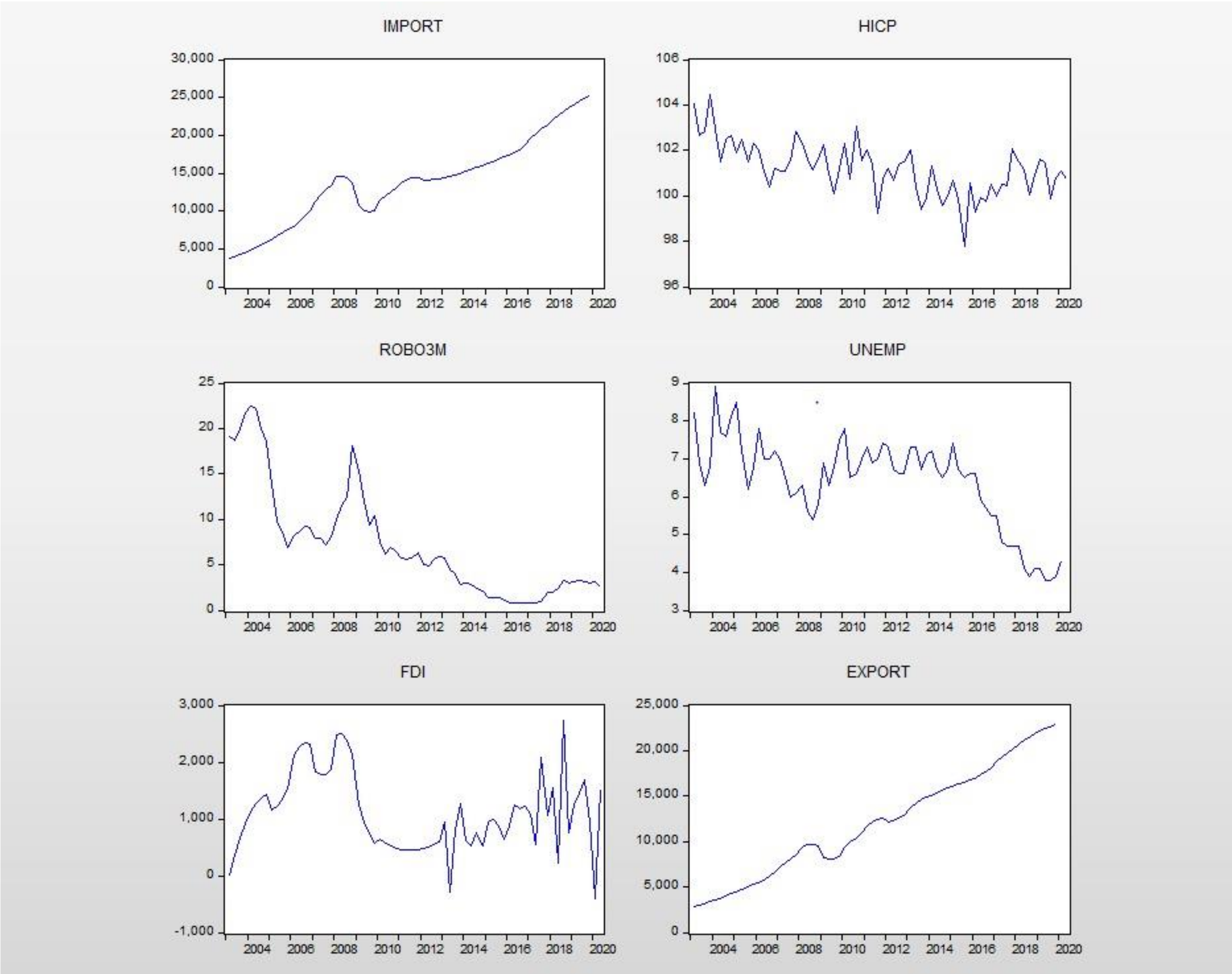
Figure 1: The Evolution of FDI and GDP during 2003Q1 – 2020Q2



Source: Own computations

During this period, several unforeseen events took place such as the economic crisis of 2008, the sovereign debt crisis on 2009-2013 or the announcement of Brexit by the United Kingdom on June 2016. These events led to a decrease of the FDI level in Romania, which also impacted the level of the economic growth. But none event compares with the appearance of first cases of coronavirus which led to a collapse in March 2020, as we can observe in Figure 1. It was the biggest shock suffered by the Romanian economy in the last 10 years, because of several factors, one of which may be the people's insecurity and uncertainty. Another quantitative factors such as import, export, the unemployment rate, harmonized index of consumer prices and ROBOR 3M, which had an impact on the romanian economy during the COVID-19 pandemic will be analyzed in the following pages.

Figure 2: Quantitative factors evolution – nonstationary



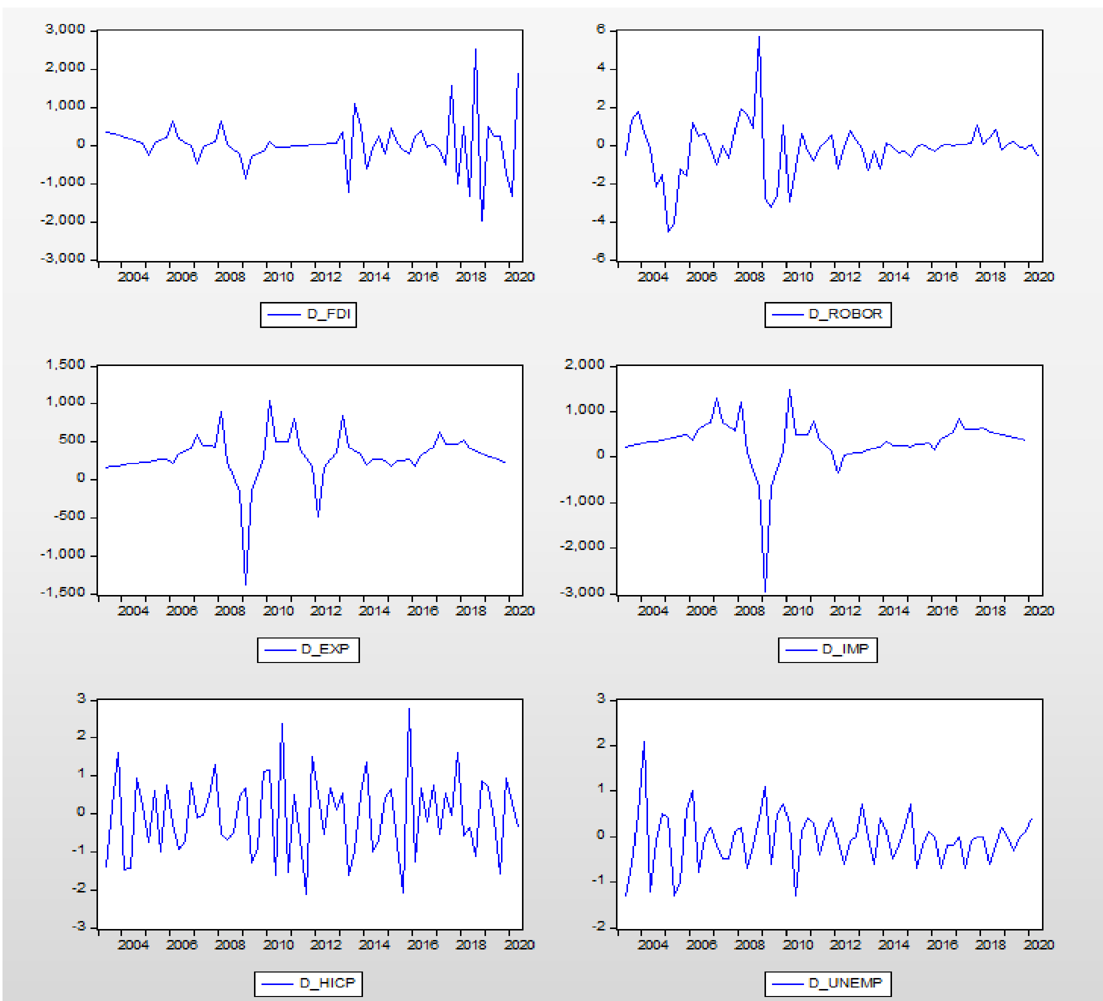
Source: Own computations

In figure 2 we can notice the evolution of the variables during the related period and see that all of them are following a certain trend, this fact being due to the no stationarity of the variables.

About of the variables we can say that the package of them represents very good the economy in Romania because the import and the export show the trade during this period and they also represent a component of GDP, the unemployment rate and the harmonized index of consumer prices are correlated in the economic theory by Philips curve, which describe an inverse relationship between the two variables. And at the last, we have the ROBOR 3M which means the rate at which the Romanian population is indebted. We can consider them relevant to illustrate the Romanian economy and to study the inter-relationship between them also how they were affected by the coronavirus crisis.

Further, will present the stationary of the variables where we eliminated their trend.

Figure 3: Quantitative factors evolution – stationary



Source: Own computations

So, figure 3 presents us the graph of the stationary variables, using first difference and we can observe that they no longer follow a certain trend as in the previous chart.

Table 1: Unit Root tests

VARIABLES	ADF	KPSS	PP
FDI	0.0001	0.247442	0.0001
Import	0.1573	0.087799	0.0009
Export	0.0460	0.090050	0.0001
HICP	0.0000	0.330761	0.0001
Unemployment rate	0.0139	0.137679	0.0000
ROBOR 3M	0.0000	0.102444	0.0000

Source: Own computations

Table 1 shows us the tests of stationarity used. As we can see, the results demonstrate that the variables used in the model are all stationary in all three tests. Exception makes the import which, according to ADF test, it turned out to be nonstationary. Therefore, in addition we performed another two stationary tests to strengthen the result (e.g. KPSS, PP) and based on them has been proved that also the import is a stationary variable.

Accordingly, these results confirm that the stationarity is not a problem anymore in our model. After the stationarity was determined, we need to identify an appropriate VAR(*p*) model for the mentioned variables.

Figure 4: Residual Serial Correlation

VAR Residual Serial Correlation LM Tests
Date: 09/28/20 Time: 21:44
Sample: 3/01/2003 6/01/2020
Included observations: 65

Null hypothesis: No serial correlation at lag h

Lag	LRE* stat	df	Prob.	Rao F-stat	df	Prob.
1	34.01065	36	0.5635	0.942282	(36, 182.8)	0.5677
2	41.88885	36	0.2305	1.184397	(36, 182.8)	0.2344
3	30.20902	36	0.7399	0.828820	(36, 182.8)	0.7431
4	47.72530	36	0.0915	1.370022	(36, 182.8)	0.0938

Null hypothesis: No serial correlation at lags 1 to h

Lag	LRE* stat	df	Prob.	Rao F-stat	df	Prob.
1	34.01065	36	0.5635	0.942282	(36, 182.8)	0.5677
2	85.43829	72	0.1331	1.218271	(72, 196.2)	0.1454
3	135.3819	108	0.0384	1.314047	(108, 173.4)	0.0548
4	196.6843	144	0.0023	1.496687	(144, 142.3)	0.0082

*Edgeworth expansion corrected likelihood ratio statistic.

Source: Own computations

To test the validity of the model it is necessary first to check the residue quality. Thus, in figure 4 we tested the presence of residual autocorrelation and the null hypothesis of the test is that the series does not show autocorrelation of the residues. As we can see in this figure, the probabilities associated with LM test for all the 4 lags are higher than the 5% significance threshold, so the residuals are not correlated with each other and the VAR (1,1) model correctly captured the dynamics of the system.

Figure 5: Stability of the model

Roots of Characteristic Polynomial
Endogenous variables: D_FDI D_ROBOR D_EXP D_IMP D_HICP D_UNEMP
Exogenous variables: C
Lag specification: 1 1
Date: 09/28/20 Time: 21:46

Root	Modulus
0.624087	0.624087
-0.616548	0.616548
0.392016 - 0.230480i	0.454750
0.392016 + 0.230480i	0.454750
-0.193987 - 0.141295i	0.239991
-0.193987 + 0.141295i	0.239991

No root lies outside the unit circle.
VAR satisfies the stability condition.

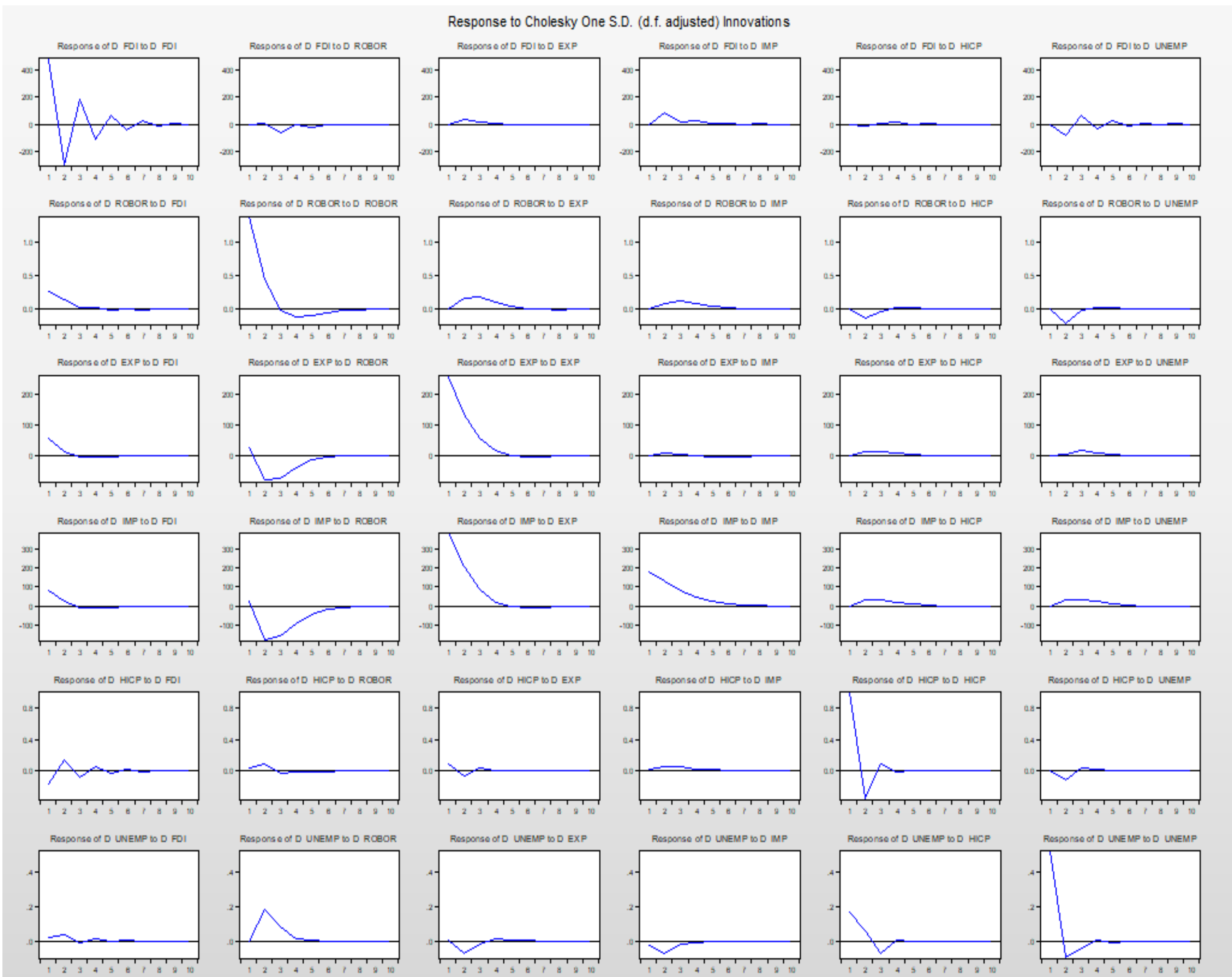
Source: Own computations

The next step in confirming the stability of the model is to check if the roots are inside the unit circle. As we can see the results from figure 5, they are all less than 1 so the conclusion is that all the roots are inside the unit circle. Based on these, we can confirm that the VAR (1,1) model is stable and the impulse response function is not explosive, so it can be studied. For a completion of the obtained results we can see the graphical representation in Appendix 2.

Regarding the residual normality test, its null hypothesis says that the residues come from a normal distribution. Thus, as presented in the figure from Appendix 1, the components of the tests are FDI, ROBOR 3M, export, import, HICP and unemployment rate, in this order. The results show us that are 2 variables in which case the null hypothesis is accepted, the export and the HICP, because their probability is greater than 5%.

Another step is studying the Granger-causality statistics which examine the prediction of one variable to another. The results of this test can be found in Appendix 4 and 5 and they tell us that the variables do not have a Ganger causality to others, only ROBOR 3M helps to predict the export, import and the unemployment rate at the 5% significance level.

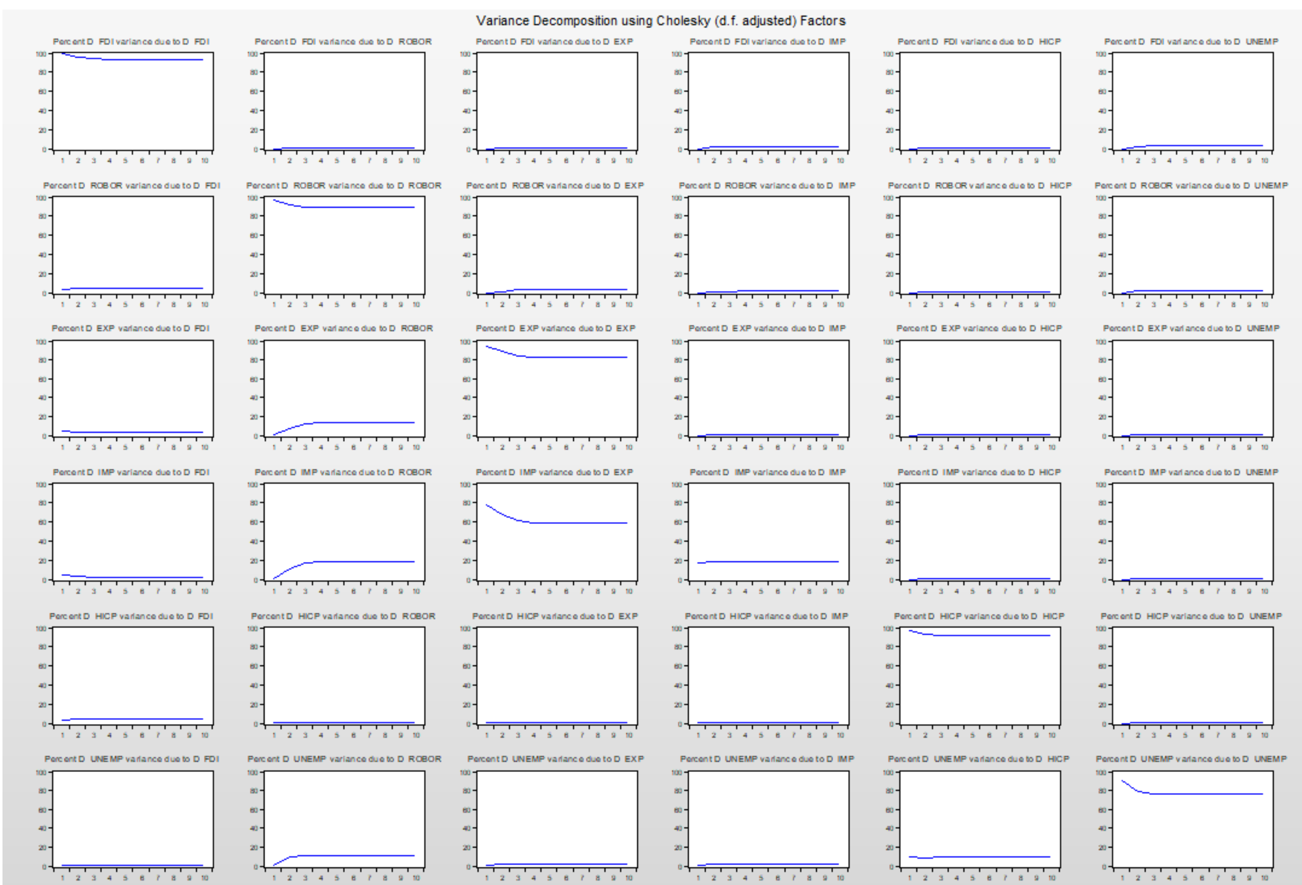
Figure 8: Impulse - response function



Source: Own computations

In figure 8 we can observe the impulse-response function which illustrates the response of present and future values of each of the variables to a one unit increase in the present value of one of the VAR (1,1) errors. In our case, a significant chart from all the above is the response of FDI to a shock on ROBOR 3M which tell us that the increase of ROBOR 3M will generate a globally decrease in loans and this will lead to a decrease in level of FDI. Also, is expected that a decrease of FDI will generate an increase of unemployment rate. Another significant chart illustrates the response of HICP to a shock from unemployment rate. These two variables are correlated by the Philips curve which says that in the short term, an unemployment increase will generate a HICP decrease due to the inflation diminution. At the last, we can affirm that the reverse relationship between unemployment and HICP leads to a decrease of the exchange rate RON/EUR. On the other hand, if the HICP would increase above the level of inflation, will expect also an increase in exchange rate because the prices of imported goods will be much higher.

Figure 9: Variance decomposition



Source: Own computations

Further we will analyze the variance decomposition which illustrates to what extent a certain variable can explain the evolution of the variant of another variable. This measures the contribution of each shock at the level of the projection error variant. In this model, the variance of an endogenous variable explains to a small extent the variance of another endogenous variable. For example, the ROBOR 3M variance explains less than 10% of the FDI variance.

Figure 10: Historical decomposition

Source: Own computations

In the end, in figure 10 we can observe the historical decomposition of the variables which represents the contribution of each innovation to each endogenous variable in the model of each historical point of time. We can see which shock was more important in determining the historical evolution of a variable. A clear shock can be observed in the case of HICP and unemployment rate, these two variables being inversely proportional.

5. Conclusions

Following the analysis, we can confirm the relationship between foreign direct investments and the economic growth. The study approves that attracting foreign capital from foreign sources is helpful for an economy even if there are some circumspect points of view to this aspect. Capital from foreign sources helps companies from the host country to develop and to adopt new technologies and managerial ideas for a better working.

Another conclusion that can be drawn is the impact of the COVID-19 pandemic which led to a decrease in the FDI inflows and by default the economic growth level. The GDP influencing factors have changed over time following the process of globalization. In our study, we found that among the most significant influencing factors counts the export and the import, the unemployment rate, the harmonized index of consumer prices also the ROBOR 3M which also represent the variables used within the VAR (1,1) model.

In order to elaborate the VAR (1,1) model we followed some ordinary steps such as the stationarity of the model, the residuals autocorrelation and the stability of the model. Following the VAR model resulted several relationships between the used variables such as the one between unemployment rate and harmonized index of consumer prices which is defined by Phillips curve like a reverse relationship. Also, we can mention again the response of FDI to a shock on ROBOR 3M which tell us that the increase of ROBOR 3M will generate a globally decrease in loans and this will lead to a decrease in level of FDI.

All this being said, we can conclude that our research paper is based on the economic theory and it wanted to illustrate the shocks suffered by the Romanian economy during 2003-2020 period also to capture the impact of the coronavirus pandemic on its economy.

Bibliography

***. (n.d.). *Documentatie Eviews 10.*

***DOFIN. (2019). *Suport curs econometrie.*

***DOFIN. (2019). *Suport seminar econometrie.*

Akoto, W. (2016). On the Nature of the Causal Relationships Between Foreign Direct Investment, GDP And Exports In South Africa. *Journal of International Development*.

Alessandro Rebucci, M. C. (2003). Bayesian VARs: A Survey of the Recent Literature with an Application to the European Monetary System. *IMF WORKING PAPERS*.

Darnel A.C, E. (1990). The Limits of Econometrics.

Faiz Muhammad Shaikh, M. S. (2010). Causality Relationship between Foreign Direct Investment, Trade and Economic Growth in Pakistan. *Asian Social Science*.

Geert Bekaert, C. H. (1990). Emerging markets finance. *Journal of Empirical Finance*.

Harvey, A. (1990). The Econometric Analysis of Time Series. *The MIT Press, Cambridge*.

Mello, L. d. (1997). Foreign Direct Investment in Developing Countries and Growth: A Selective Survey. *OECD*.

Radu CIOBANU, R.-A. Ş. (2020). The Impact of FDI over Economic Growth and how COVID-19 Crisis. *CECCAR BUSINESS REVIEW*, 64-72.

Robert Inman, D. R. (1997). *Rethinking Federalism.* Journal of Economic Perspectives.

Ross Levine, M. C. (2002). Finance and growth: New evidence and policy analyses for Chile. *Central Bank of Chile*.

Rubens de S Duarte, M. R. (2017). Politicising financial foreign policy: an analysis of Brazilian foreign policy formulation for the financial sector. *Revista Brasileira de Politica Internacional*.

Sims, C. (1980). *Vector Autoregressions.*

Suliman, E. A. (2018). Endogenous Specification of FDI and Economic Growth: Cross-Economies Evidene. *International Journal of Business*, 89-109.

Verbeek, M. (n.d.). *A guide to Modern Econometrics. 2nd Edition.*

Werner, R., & Carbonell, J. B. (2018). Does Foreign Direct Investment Generate Economic Growth? A New Empirical Approach Applied to Spain.

Appendix

Appendix 1: Residual Normality Test

VAR Residual Normality Tests
Orthogonalization: Cholesky (Lutkepohl)
Null Hypothesis: Residuals are multivariate normal
Date: 09/28/20 Time: 21:45
Sample: 3/01/2003 6/01/2020
Included observations: 66

Component	Skewness	Chi-sq	df	Prob.*
1	0.595292	3.898094	1	0.0483
2	0.645465	4.582878	1	0.0323
3	-0.180218	0.357264	1	0.5500
4	-1.600444	28.17563	1	0.0000
5	-0.188778	0.392008	1	0.5312
6	1.262845	17.54255	1	0.0000
Joint		54.94842	6	0.0000

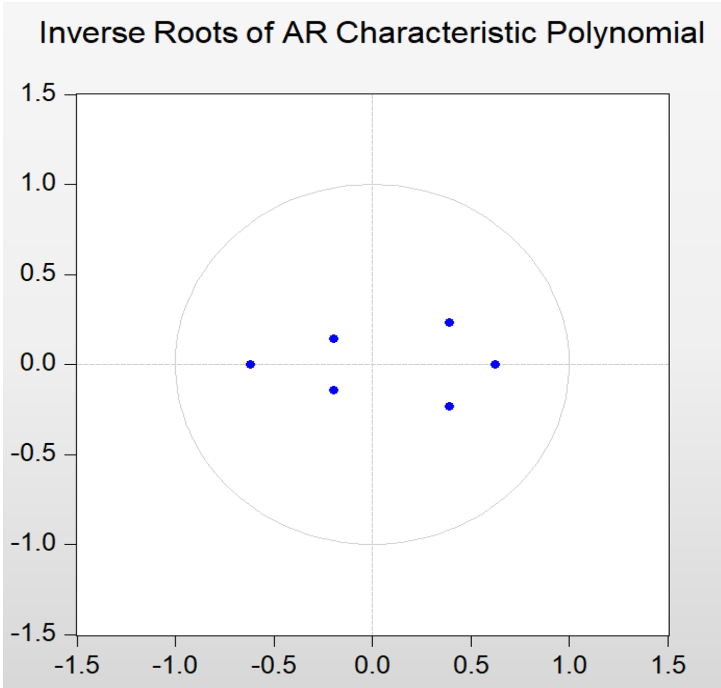
Component	Kurtosis	Chi-sq	df	Prob.
1	4.344624	4.972035	1	0.0258
2	9.004929	99.16273	1	0.0000
3	6.754595	38.76670	1	0.0000
4	9.784358	126.5756	1	0.0000
5	2.864961	0.050148	1	0.8228
6	5.640893	19.17937	1	0.0000
Joint		288.7066	6	0.0000

Component	Jarque-Bera	df	Prob.
1	8.870129	2	0.0119
2	103.7456	2	0.0000
3	39.12397	2	0.0000
4	154.7513	2	0.0000
5	0.442156	2	0.8017
6	36.72192	2	0.0000
Joint	343.6551	12	0.0000

*Approximate p-values do not account for coefficient estimation

Source: Own computations

Appendix 2: Stability of the model



Source: Own computations

Appendix 3: Residuals

Source: Own computations

Appendix 4: Granger causality (1)

Dependent variable: D_FDI

Excluded	Chi-sq	df	Prob.
D_ROBOR	0.020947	1	0.8849
D_EXP	1.355853	1	0.2443
D_IMP	2.998982	1	0.0833
D_HICP	0.032701	1	0.8565
D_UNEMP	1.943046	1	0.1633
All	7.547121	5	0.1830

Dependent variable: D_ROBOR

Excluded	Chi-sq	df	Prob.
D_FDI	0.019945	1	0.8877
D_EXP	0.000524	1	0.9817
D_IMP	0.436977	1	0.5086
D_HICP	0.190687	1	0.6623
D_UNEMP	1.569003	1	0.2104
All	5.579670	5	0.3493

Dependent variable: D_EXP

Excluded	Chi-sq	df	Prob.
D_FDI	0.003736	1	0.9513
D_ROBOR	8.743560	1	0.0031
D_IMP	0.156717	1	0.6922
D_HICP	0.104293	1	0.7467
D_UNEMP	0.047067	1	0.8282
All	9.120201	5	0.1044

Source: Own computations

Appendix 5: Granger causality (2)

Dependent variable: D_IMP

Excluded	Chi-sq	df	Prob.
D_FDI	0.183710	1	0.6682
D_ROBOR	13.26113	1	0.0003
D_EXP	0.574588	1	0.4484
D_HICP	0.224366	1	0.6357
D_UNEMP	0.411932	1	0.5210
All	14.47567	5	0.0129

Dependent variable: D_HICP

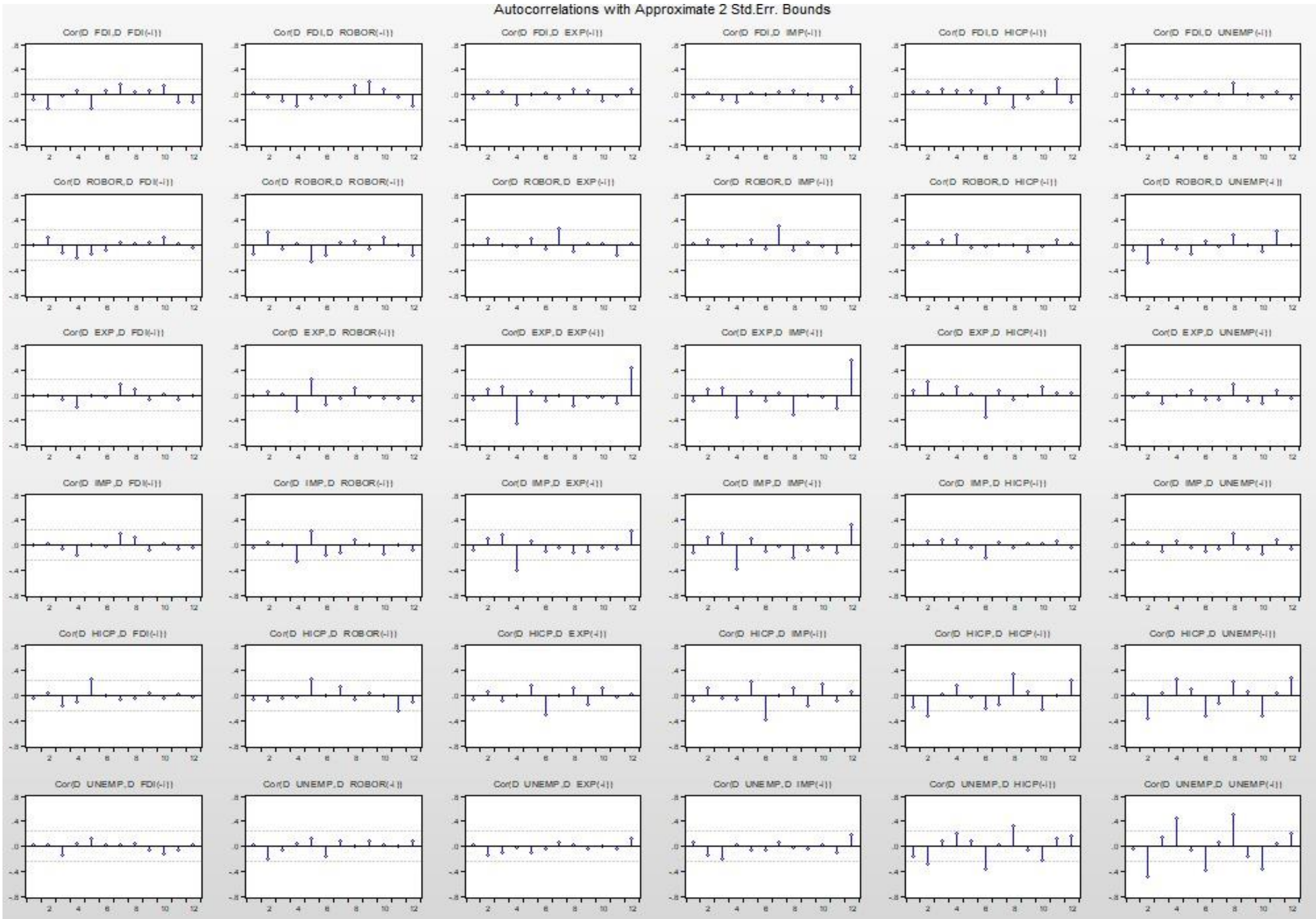
Excluded	Chi-sq	df	Prob.
D_FDI	0.480826	1	0.4880
D_ROBOR	0.624847	1	0.4293
D_EXP	0.444832	1	0.5048
D_IMP	0.360912	1	0.5480
D_UNEMP	0.912873	1	0.3394
All	2.729484	5	0.7416

Dependent variable: D_UNEMP

Excluded	Chi-sq	df	Prob.
D_FDI	0.421348	1	0.5163
D_ROBOR	7.822662	1	0.0052
D_EXP	0.402907	1	0.5256
D_IMP	2.074653	1	0.1498
D_HICP	1.696112	1	0.1928
All	13.73821	5	0.0174

Source: Own computations

Appendix 6: Residual Correlograms



Source: Own computations

Forecasting CDS volatility : A comparison of GARCH-class models

Roxana-Gabriela Mozolea

Alexandru Ioan Cuza University, Faculty of Economics and Business Administration, Iasi

Abstract

Keywords: European CDS; Forecasting volatility; GARCH-class models; CEE vs. WE countries

JEL Classification: C53,G15, G17

Length in pages: 24

This paper aims to analyze the European Union (EU) sovereign CDSs in terms of forecasting volatility performance of six selected GARCH-class models. Considering that EU countries have different behaviors in terms of financial market activity, different levels of sovereign default risk and different political and economic stability, it is important to analyze the volatility of the Central and Eastern European (CEE) countries versus Western European (WE) countries and to test if there is one single GARCH-class model that outperforms the rest or if there are different models according to the Central-East/West delimitation.

The choice in using GARCH-class models as forecasting instruments is due to their predictive power and their capability to forecast the volatility of numerous financial instruments, commodities, or stocks. I have selected 6 GARCH models (GARCH (1,1), EGARCH, APARCH, GJR-GARCH, TGARCH, and IGARCH) due to their particular advantages when forecasting financial instruments. The steps of my research consist of analyzing descriptive statistics of the CDS spreads and the log-returns, choosing to use log-returns due to normalization, using ADF unit root test to test the presence of a unit root, applying ARCH LM test to discover if data present ARCH effects so I can test the selected GARCH-class models and, finally, to apply the criteria for the results of the six GARCH-class models (LL, AIC, SIC, and HQIC).

The results showed that for the 30 days out-of-sample period, GJR-GARCH model outperformed the rest, for the 90 days out-of-sample period, both GARCH (1,1) and IGARCH were the most appropriate models and the 180 days out-of-sample values present GARCH (1,1) as the best model for the majority of the selected countries. Regarding the CEE/WE delimitation, the CDS volatility of countries from CEE is better forecasted by GARCH (1,1) in all the out-of-sample periods, while the CDS volatility of countries from WE has different outperformers according to the out-of-sample period: for 30 days out-of-sample period the best model is GJR-GARCH, for 90 days out-of-sample are both GJR-GARCH and IGARCH and for the 180 days out-of-sample period is APARCH.

Introduction

Forecasting the volatility of financial instruments has always been an engaging research topic considering prediction as an important tool in managing market risk, one of the major risks for banks, investors and financial institutions.

Credit Default Swap (CDS) is the most widely used type of credit derivative and it is a transaction in which the buyer transfers the risk of a credit event to the seller, in exchange for a period premium payment. CDSs are often used in hedging risk, arbitrage, or even in making profit, for example if the risk is underpriced. CDS spreads are widely analyzed from the development and influence perspective but there is a gap in this research field on the **forecasting performance**, especially on the **sovereign European CDSs**. The instruments used in the research are **GARCH-class models** due to their predictive power and their capability to forecast the volatility of numerous financial instruments, commodities or stocks.

The motivation of this research can be divided according to two objectives: firstly, to see if one of the stated GARCH models is outperforming the rest by analyzing each country from the EU, and secondly, to divide the countries by **Central-East/West partition** and to analyze if there exists one better model for all or if there are differences in terms of forecasting performances. In order to assess the prediction fitness, there are used four different **criteria tests**: LL, AIC, SIC and HQIC.

Credit default swaps are contracts that offer credit protection, in return of a periodic premium, in the case of a predefined event. The international quoting convention implies an annual premium set as a specific percentage of the notional amount of the obligation. The CDS market brings advantages for both sides: the buyers of the protections reduce credit concentration while sellers, without funding the position, increase the income by taking credit exposure. CDSs are the invention of JP Morgan in 1994 in order to reduce excess credit risk and increase the loan capabilities for commercial banks (Girish, 2010).

One of the first CDS written by JP Morgan was to offer a credit line of $5 billion to Exxon without decreasing the flexibility of the balance sheet. JP Morgan sold the credit risk to the European Bank of Reconstruction and Development, paid a periodic fee and received the credit insurance from the bank.

CDS contracts can be majorly divided according to two perspectives:

- by reference entity number: one entity (single-name CDSs) or multiple entities (multi-name CDSs)

- by reference entity type: corporate or sovereign

Single-name CDSs provide protection for a single entity, either sovereign or corporate, while multi-name CDSs reference multiple entities, including index products, basket products and CDS tranches. The most recent report from Bank for International Settlements (BIS) showed that, at the end of June 2019, the notional amount of CDS contracts of $7.8 trillion, with 4.1% less than one year before. Single-name CDS notional amount declined with 9.4% and multi-name CDS notional amount increase by 1% , compared with the end of June, 2018.

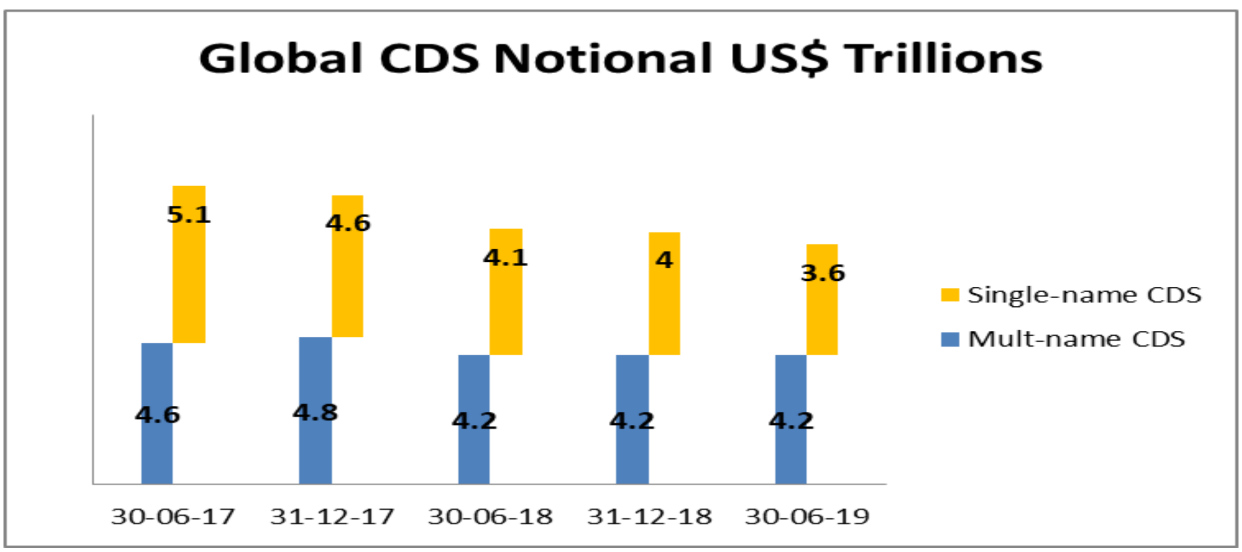


Figure 1: Global CDS Notional in US$ Trillion
Source: Bank of International Settlements November 2019 Report

Even though both corporate and sovereign CDS types are developed in order to protect against a credit event, there are also important differences between those two: purpose, credit events that trigger the payment and currency in which contracts are denominated. For example, according to Fontana and Scheicher (2010), the sovereign CDSs can be used also for hedging against country risk, combining short and long positions in two different countries and apply arbitrage trading by buying or selling both corporate bonds and CDS contracts. In a report published in November 2019 by International Swaps and Derivative Association (ISDA), it shows the evolution of single-name CDS market activity by reference entity type. The 2nd quarter of 2019 shows a decrease of $0.2 trillion in the market activity of corporate CDSs and a decrease of $0.1 trillion in the market activity of sovereign CDSs. On the other hand, the last quarter of 2018 shows similar values as the 2nd quarter of 2019. We can observe a higher fluctuation in sovereign CDSs than corporate ones.

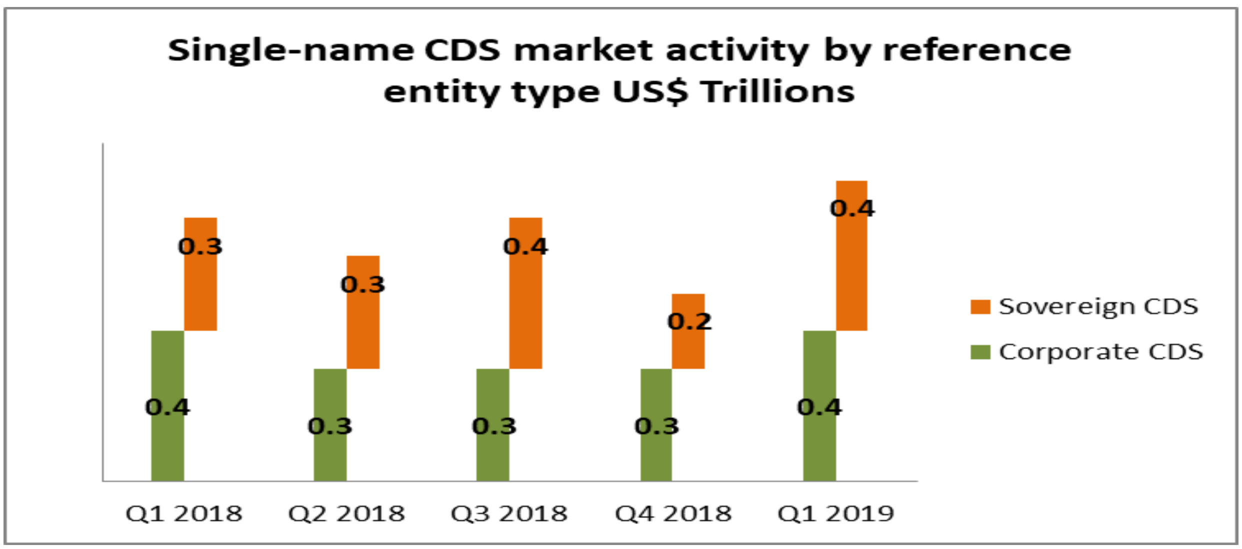


Figure 2: Single-name CDS market activity by reference entity type in US$ Trillion

Source: ISDA September 2019 Report

Literature review

Engle (1982) developed the famous **ARCH** (Autoregressive Conditional Heteroscedasticity) model, an accurate design in forecasting financial time series by connecting the variance of the current error term with the size of the previous ones. Four years later, Tim Bollerslev upgraded the ARCH model to a generalized form called **GARCH** (Generalized Autoregressive Conditional Heteroscedasticity) that is a better fit for data with heteroskedasticity and volatility clustering. This was the starting point of numerous GARCH models that developed later with unique characteristics and differences.

Engle and Bollerslev (1986) introduced an integrated GARCH model (**IGARCH**) that keeps variance persistent as information of today is important in estimations for all horizons. Nelson (1991) the exponential GARCH (**EGARCH**) model that allows the conditional volatility to have asymmetric relation with past data, happening usually when there is an abrupt drop in stock price caused by bad news that increases volatility more than in the case of an abrupt increase due to good news.

Two years later, Glosten, Jaganathan and Runkle (1993) developed a new GARCH model, the **GJR** (Glosten-Jagannathan-Runkle) one that allows the conditional variance to act following past positive and negative innovations. Also, it gathers the asymmetric shocks, both positive and negative, and adds a multiplicative dummy variable to check whether there is statistically significant considering the variation of the shocks.

In the same year, Ding, Grange, and Engle extended the ARCH model to the asymmetric power version, the **APARCH**, similar to the GJR-GARCH model that captures the differences in return volatility but also yield the long-memory property of returns.

Zakoian (1994) developed the **TGARCH** (Threshold GARCH) model that is very similar to the GJR-GARCH, the only difference being that the variance was replaced with the standard deviation.

Due to their predictive power, GARCH class models have been intensively used in forecasting volatility of different financial instruments. Most of the studies are focused on stock markets (Gökbulut and Pekkay, 2014; Srinivasan and Ibrahim, 2010; Onwukwe et al, 2011; Liu and Hung, 2010; Pillbeam and Langeland, 2015), exchange rates (Cheong Vee et al., 2011;) or commodity markets like oil (Agnolucci, 2009; Kang et al., 2009; Wei et al., 2010; Mohammadi and Su, 2010; Wang et al., 2010;) or energy markets, metals and corn (Shen and Ritter, 2016; Bentes, 2015; Musunuru et al., 2013).

The main study used as a reference and as starting point in this research is an article by S. Sabkha, C. de Peretti and D. Hmaied published in 2018. Their main objective was to develop specialized literature and to study also the GARCH model performance in predicting sovereign CDS. They used a dataset that consists of daily 5-year sovereign CDS spreads from 38 worldwide countries from five geopolitical regions: Western and Eastern Europe, North and South America and Asia. In their analysis they tested 9 univariate GARCH models (GARCH (1,1), EGARCH, GJR-GARCH, APARCH, IGARCH, FIGARCH, FIEGARCH, FIAPARCH and HYGARCH) by applying in and out of sample methodology (from 2014 to 2017 was the out-of-sample dataset). The ranking in terms of predicting performance was set by seven information criteria: MSE, MAE, HMSE, HMAE, QLIKE, MLAE and R^2LOG. The results showed that non-linear models are better in out-of-sample predictions due to leverage effects, long-memory behavior and the asymmetric dependencies in the volatility process. From the tested ones, the FIGARCH and FIEGARCH models outperformed the rest in forecasting sovereign CDS volatility in the out-of-sample dataset but in the in-the-sample dataset, no model appeared to be more accurate than the rest for the selected countries.

Data

The database used for this study consists of daily 5-year sovereign CDS spreads denominated in euros for almost all European Union countries, having some exceptions: Finland, Malta and Netherlands do not have sovereign CDSs denominated in euro, Greece stopped having CDSs denominated in euro since 2018 and Luxemburg which was excluded due to liquidity issues. The data was retrieved from the Thomson Reuters platform for a period of almost ten years, from 28th April 2009 and 31st December 2019, this timeframe being selected according to the availability of liquid data. The delimitation between Western and Central and Eastern European (CEE) Union countries was made as follows: in the Western sample I have included Belgium, France, Germany, Italy, Denmark, Ireland, United Kingdom (even though UK has left European Union on 31st January 2020, it was still a member country during my database timeframe), Portugal, Spain, Austria, Sweden. The CEE Union countries (according to the European Commission, 2015) are: Czech Republic, Estonia, Latvia, Lithuania, Hungary, Poland, Slovenia, Slovakia, Cyprus, Bulgaria, Romania and Croatia.

Objectives and methodology

The main objective of this study is to assess GARCH-class models forecasting performance of European Union sovereign CDS volatility and to select which models outperform the rest. Considering that European Union countries have different behaviors in terms of financial market activity, different levels of sovereign default risk and different political and economic stability, the second objective is to analyze the Central and Eastern European Union countries versus Western European Union countries in terms of volatility and to test if there is one single GARCH-class model that outperforms the rest or if there are different models according to the Central-East/West delimitation.

Considering the lack of studies on this exact topic and that the research topic focuses on exploratory, not explanatory, reasons, it is very difficult to create certain hypotheses.

Nevertheless, by analyzing the previous articles, we can observe that there is not a single GARCH-class models that outperforms the rest; they are different according to the type of financial instrument, commodity or stock they forecast or different in terms of national financial development and economic growth.

The first hypothesis is that there won't be a single most appropriate GARCH-class model, but there would be different models for certain countries. I consider the empirical results would rather be in terms of majority best, not in absolute best.

Regarding my second objective, it is very important to take into consideration that volatility in Central and Eastern European Union countries is significantly higher, so the second hypothesis is that for Central and Eastern European Union sovereign CDSs there will be one GARCH-class model better in forecasting the volatility and for the West European Union sovereign CDSs there will be a different one.

With respect to some representative studies related to this research (Agnolucci, 2008; Wei et al., 2010; Srinivasan and Ibrahim, 2010; Bouri et al., 2017; Sabkha, 2018), I have selected 6 univariate GARCH-class models: GARCH (1,1), EGARCH, GJR-GARCH, APARCH, TGARCH and IGARCH. These models are among the most popular and widely used GARCH-class models in forecasting the volatility of financial instruments.

The general **GARCH (p, q)** model states that variance is influenced by its past values and by the past values of the shocks which are captured by lagged terms and, respectively, residuals. It has the following formula:

$$x_{i,t} = \mu_{i,t} + u_{i,t} \quad \text{where} \quad u_{i,t} = \sigma_{i,t}\varepsilon_{i,t}$$

$$\sigma_{i,t}^2 = \alpha_{i,0} + \sum_{k=1}^{q_i} \alpha_{i,k}\, a_{i,t-1}^2 + \sum_{h=1}^{p_i} \beta_{i,h}\, \sigma_{i,t-1}^2$$

Where $x_{i,t}$ is a financial time series, *i* is a given country from the sample and $u_{i,t}$ and $\sigma_{i,t}$ are respectively conditional mean and conditional volatility.

GARCH (1,1) model is based on the assumption that forecasts of time varying variance depend on the lagged variance of the asset. An unexpected increase or decrease in returns at time t will generate an increase in the expected variability in the next period and it has the following formula:

$$\sigma_{i,t}^2 = \alpha_{i,0} + \alpha_{i,1} + \alpha_{i,1} a_{i,t-1}^2 + \beta_{i,1}\sigma_{i,t-1}^2$$

IGARCH model developed by Engle and Bollerslev, keeps the variance persistent and the main difference, compared to GARCH (1,1), is that parameters α and β, when summed, must equal 1. It can be translated as following:

$$\sigma_{i,t}^2 = \alpha_{i,1} a_{i,t-1}^2 + (1 - \alpha_{i,1})\sigma_{i,t-1}^2$$

The Exponential GARCH (**EGARCH**) model proposed by Nelson (1991) is specifically designed to capture the asymmetry shock to the conditional variance. In the EGARCH model the natural logarithm of the conditional variance is allowed to vary over time as a function of the lagged error terms rather than lagged squared errors.

$$\ln(\sigma_{i,t}^2) = \alpha_{i,0} + \alpha_{i,1-1}\ln(\sigma_{i,t}^2) + \beta_{i,1} g(\varepsilon_{i,t-1}) \text{ where}$$

$$g(\varepsilon_{i,t}) = \theta_i \varepsilon_{i,t} + \gamma_i[|\varepsilon_{i,t}| - E(|\varepsilon_{i,t}|)]$$

Glosten et al. (1993) proposed a model that allows the sign and the amplitude of the innovations to affect the conditional volatility separately, **GJR-GARCH**. The asymmetric leverage effect is represented in the following formulation of the GJR-GARCH model:

$$\sigma_{i,t}^2 = \alpha_{i,0} + \alpha_{i,1} a_{i,t-1}^2 + \gamma_i I_{i,t-1} a_{i,t-1}^2 + \beta_{i,1}\sigma_{i,t-1}^2$$

where I_t, a dummy variable, equals to 0 when a_t is positive and 1 otherwise.

APARCH model (Ding et al., 1993) is the first GARCH model developed to take into consideration the long-range persistence of financial assets variance. The volatility can be long-memory and it has the following formula:

$$\sigma_{i,t}^2 = \alpha_{i,0} + \alpha_{i,1}(|a_{i,t-1}^2| - \gamma_i a_{i,t-1})^{\delta} + \beta_{i,1}\sigma_{i,t-1}^{\delta}$$

TGARCH model developed by Zakoian (1994) is unique by using standard deviation instead of using variance:

$$\sigma_{i,t} = \alpha_{i,0}+\alpha_{i,1}\sigma_{i,t-1}(|a_{i,t-1}| - \gamma_i a_{i,t-1}) + \beta_{i,1}\sigma_{i,t-1}$$

The forecasting process of the CDS volatility has followed the study of Wei et al. (2010): the CDS times series' timeline is divided into two sub periods: the in-sample volatility estimation is conducted from 28th April, 2009 to December 31st, 2018 and the out-of-sample model forecasts that focus on last two years, from January 1st, 2019 to December 31st, 2019, with 30 days, 90 days and 180 days forecasting period.

The performance of a model over another one cannot be decided considering a single error statistic since each criterion may be more and less relevant from one case to another. Following the methodology from several studies (Gökbulut and Pekkay, 2014; Srinivasan and Ibrahim, 2010; Bouri et al, 2017), there will be used four values that will determine the best GARCH model in forecasting CDS volatility: Log Likelihood, Akaike Info criterion, Schwarz criterion and Hannan-Quinn criterion.

Log Likelihood (LL) estimation is a method that determines values for the parameters of a model. The parameter values are found such that they maximize the likelihood that the process described by the model produced the data that were actually observed.

Akaike information criterion (AIC) is a fined technique based on in-sample fit to estimate the likelihood of a model to predict/estimate the future values.

The Schwarz Criterion (SBIC) is a measure to help in the selection between candidate models. Using this criterion, the best model is the one with the lowest SC. This criterion takes into account both the closeness of fit of the points to the model and the number of parameters used by the model.

The Hannan-Quinn information criterion (HQIC) is a measure of the goodness of fit of a statistical model and is often used as a criterion for model selection among a finite set of models.

Results

Descriptive statistics are brief descriptive coefficients that summarize a given data set. Table 3. and Table 4. present the descriptive statistics for the CDS spreads and for the returns that were calculated as $\ln(premium_t/premium_{t-1})$.

By analyzing the descriptive statistics in Table 1. of the sovereign CDS spreads, it can be observed that the selected countries present different levels of credit risks, this being demonstrated by the CDS spreads that vary from 5 bp (Germany) to 1674.22 bp (Cyprus) and by the mean of the daily CDS spreads ranging from 18.17 bp (Germany) to 411.06 bp (Cyprus).Standard deviation values show that there are important differences between the analyzed sovereign markets in terms of volatility: the least volatile CDS market is Germany (14.57 bp) and the most volatile CDS market is Cyprus (387.52 bp).

Table 1: Descriptive statistics of CDS spreads

Variable	Obs	Mean	Std. Dev	Min	Max
Austria CDS spread	2,786	34.18	32.98	5.76	159.23
Belgium CDS spread	2,786	54.92	59.46	7.86	341.98
Bulgaria CDS spread	2,786	155.72	82.56	59.59	427.65
Croatia CDS spread	2,786	237.11	101.98	55.47	559.69
Cyprus CDS spread	2,786	411.06	387.52	70.00	1674.22
Czech Republic CDS spread	2,786	60.78	29.64	30.92	177.91
Denmark CDS spread	2,786	26.54	28.85	5.04	147.06
Estonia CDS spread	2,786	83.91	56.98	42.92	442.50
France CDS spread	2,786	38.02	32.58	5.74	171.56
Germany CDS spread	2,786	18.17	14.57	5.00	79.29
Hungary CDS spread	2,786	205.83	123.43	67.41	661.24
Ireland CDS spread	2,786	166.15	216.70	11.43	1191.16
Italy CDS spread	2,786	141.92	93.22	42.04	498.66
Latvia CDS spread	2,786	160.22	158.02	38.45	791.30
Lithuania CDS spread	2,786	137.48	103.97	41.72	570.00
Poland CDS spread	2,786	93.48	49.49	43.51	300.89
Portugal CDS spread	2,786	279.37	297.20	20.39	1521.45
Romania CDS spread	2,786	177.09	99.19	64.93	438.35
Slovakia CDS spread	2,786	74.68	55.61	34.87	285.15
Slovenia CDS spread	2,786	133.43	95.80	48.00	448.67
Spain CDS spread	2,786	120.59	103.32	13.54	492.07
Sweden CDS spread	2,786	19.82	15.87	5.64	82.50
UK CDS spread	2,786	37.12	21.05	10.76	102.00

Table 2. presents the descriptive statistics of the log-returns of the CDS spreads. The log-returns are better than the raw CDS spreads in terms of normalization, measuring all variables in a comparable metric, and it is easier for calculations and tests in a time series type of data.

Table 2. Descriptive statistics of log returns CDS spreads

Variable	Obs	Mean	Std. Dev	Min	Max
Return Austria CDS spread	2,786	-0.001079	0.045259	-0.456027	0.401864
Return Belgium CDS spread	2,786	-0.000790	0.048205	-0.335181	0.322328
Return Bulgaria CDS spread	2,786	-0.000633	0.024387	-0.319506	0.291857
Return Croatia CDS spread	2,786	-0.000625	0.022266	-0.248896	0.232351
Return Cyprus CDS spread	2,786	-0.000144	0.033471	-0.460665	0.406762
Return Czech Republic CDS spread	2,786	-0.000535	0.024907	-0.318454	0.302281
Return Denmark CDS spread	2,786	-0.000876	0.062717	-0.339902	0.339902
Return Estonia CDS spread	2,786	-0.000782	0.024491	-0.193091	0.200671
Return France CDS spread	2,786	-0.000659	0.048332	-0.265987	0.467399
Return Germany CDS spread	2,786	-0.000767	0.062500	-0.507129	0.590115
Return Hungary CDS spread	2,786	-0.000680	0.023494	-0.240535	0.272536
Return Ireland CDS spread	2,786	-0.001010	0.032424	-0.331071	0.253736
Return Italy CDS spread	2,786	-0.000221	0.041783	-0.451978	0.332625
Return Latvia CDS spread	2,786	-0.000953	0.020129	-0.216244	0.165954
Return Lithuania CDS spread	2,786	-0.000847	0.020002	-0.230202	0.156843
Return Poland CDS spread	2,786	-0.000547	0.027736	-0.336472	0.245449
Return Portugal CDS spread	2,786	-0.000428	0.040606	-0.590042	0.305382
Return Romania CDS spread	2,786	-0.000666	0.021226	-0.222876	0.225297
Return Slovakia CDS spread	2,786	-0.000440	0.028329	-0.287682	0.275706
Return Slovenia CDS spread	2,786	-0.000224	0.026457	-0.223144	0.274437
Return Spain CDS spread	2,786	-0.000563	0.048670	-0.550790	0.523923
Return Sweden CDS spread	2,786	-0.000892	0.082875	-0.513925	0.532126
Return UK CDS spread	2,786	-0.000739	0.050824	-0.479610	0.283635

As evidence, Figure 3. shows, in a graphical format, the fluctuations of the spreads and of the returns over the selected time frame (2009-2019). The CDS spreads graphs look noisy (many fluctuations), while the log-returns graphs are smoother. Considering the arguments presented above, the log-returns of CDS spreads will be used further in the research.

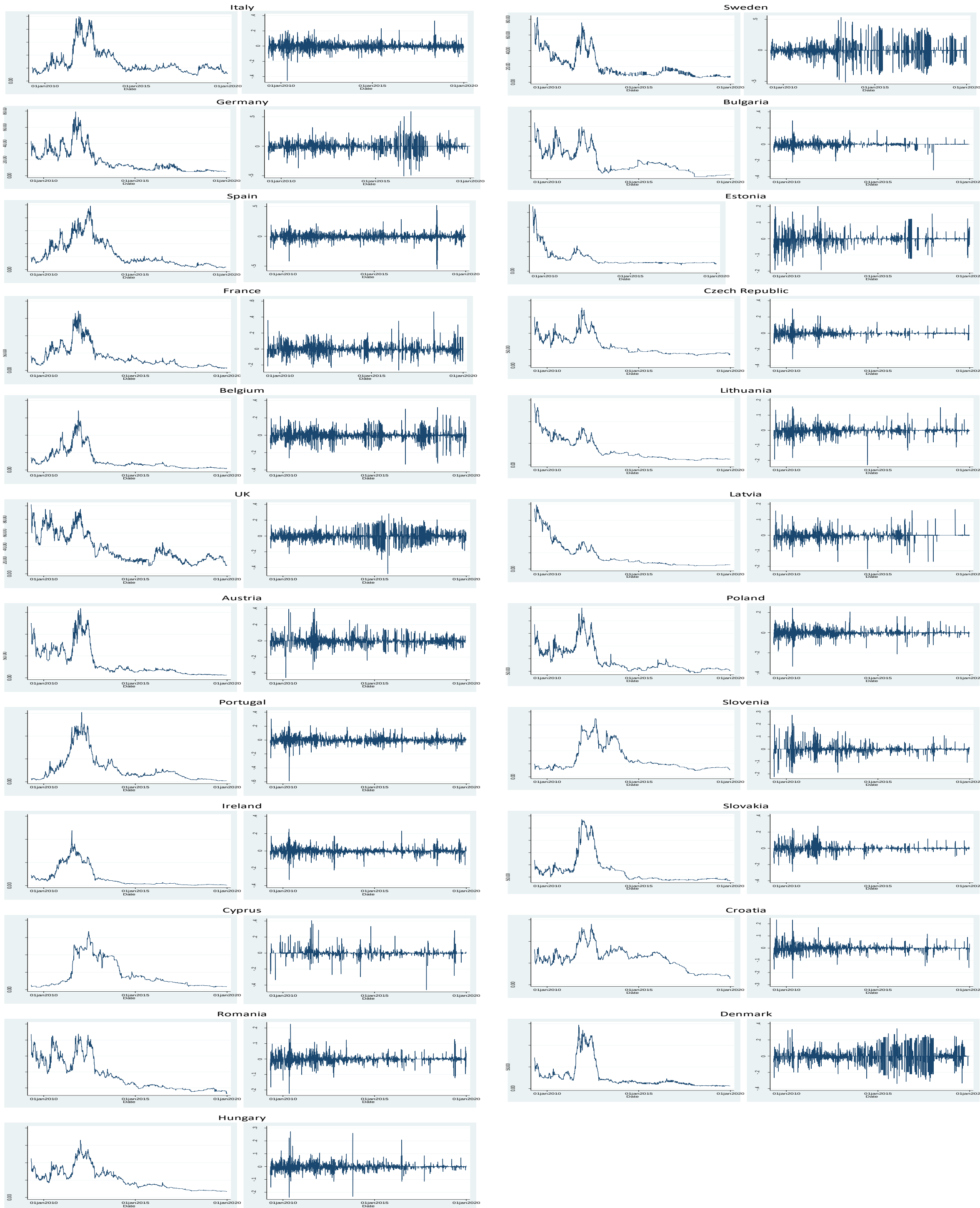


Figure 3. Graphs of CDS spreads and returns

In order to test if the time series present a unit root, I have applied the Augmented Dickey Fuller-Test (ADF), a procedure developed by Dickey and Fuller in 1979. The null hypothesis is that the data has a unit root. Table 3. presents the test statistics and the critical values, from which it is overwhelmingly clear that the null hypothesis of unit root presence is rejected.

Table 3. ADF Unit Root Test Results

Variable	Test Statistic	1% Critical value	5% Critical value	10% Critical value
Return Austria CDS spread	-50.37	-3.43	-2.86	-2.57
Return Belgium CDS spread	-51.87	-3.43	-2.86	-2.57
Return Bulgaria CDS spread	-40.53	-3.43	-2.86	-2.57
Return Croatia CDS spread	-41.43	-3.43	-2.86	-2.57
Return Cyprus CDS spread	-51.15	-3.43	-2.86	-2.57
Return Czech Republic CDS spread	-44.73	-3.43	-2.86	-2.57
Return Denmark CDS spread	-61.87	-3.43	-2.86	-2.57
Return Estonia CDS spread	-51.75	-3.43	-2.86	-2.57
Return France CDS spread	-48.14	-3.43	-2.86	-2.57
Return Germany CDS spread	-55.47	-3.43	-2.86	-2.57
Return Hungary CDS spread	-41.70	-3.43	-2.86	-2.57
Return Ireland CDS spread	-43.19	-3.43	-2.86	-2.57
Return Italy CDS spread	-38.18	-3.43	-2.86	-2.57
Return Latvia CDS spread	-47.57	-3.43	-2.86	-2.57
Return Lithuania CDS spread	-44.09	-3.43	-2.86	-2.57
Return Poland CDS spread	-39.53	-3.43	-2.86	-2.57
Return Portugal CDS spread	-37.27	-3.43	-2.86	-2.57
Return Romania CDS spread	-43.62	-3.43	-2.86	-2.57
Return Slovakia CDS spread	-50.32	-3.43	-2.86	-2.57
Return Slovenia CDS spread	-46.78	-3.43	-2.86	-2.57
Return Spain CDS spread	-50.71	-3.43	-2.86	-2.57
Return Sweden CDS spread	-65.16	-3.43	-2.86	-2.57
Return UK CDS spread	-62.35	-3.43	-2.86	-2.57

Autoregressive conditional heteroscedastic (ARCH) effects are observed in time series that exhibit conditional heteroscedasticity – or autocorrelation in the squared series. Engle’s ARCH test is a Lagrange multiplier test to assess the significance of ARCH effects.

I have tested up to four lags, the maximum allowed by my data series (and the program). As presented in Table 4., all the tested returns present ARCH effects, excepting Cyprus and Germany when testing with four lags. Considering that for the first three lags these countries present ARCH effects and because the values are not very high (0.09 and 0.06) compared with the critical value of 0.05, I have decided to keep them and test the GARCH model on them too.

Table 4. ARCH LM Test Results

Variable	Lags(1)		Lags(2)		Lags(3)		Lags(4)	
	Chi2	PProb>Chi2	Chi2	PProb>Chi2	Chi2	PProb>Chi2	Chi2	Prob>Chi2
Return Austria CDS spread	10.7140	0.0011	9.1220	0.0105	10.0340	0.0183	60.9590	0.0000
Return Belgium CDS spread	372.3970	0.0000	260.1770	0.0000	222.5090	0.0000	138.4540	0.0000
Return Bulgaria CDS spread	19.1970	0.0000	161.2700	0.0000	162.1730	0.0000	93.5760	0.0000
Return Croatia CDS spread	24.5440	0.0000	216.5100	0.0000	234.3500	0.0000	193.5220	0.0000
Return Cyprus CDS spread	5.9570	0.0147	10.1730	0.0062	21.9400	0.0001	7.9270	0.0943
Return Czech Republic CDS spread	27.9080	0.0000	378.9630	0.0000	433.7070	0.0000	369.3260	0.0000
Return Denmark CDS spread	257.4790	0.0000	205.9680	0.0000	121.1910	0.0000	108.5610	0.0000
Return Estonia CDS spread	33.5250	0.0000	100.0160	0.0000	101.9280	0.0000	117.4230	0.0000
Return France CDS spread	29.0180	0.0000	43.8760	0.0000	46.1620	0.0000	27.1810	0.0000
Return Germany CDS spread	146.0670	0.0000	18.4100	0.0001	20.3290	0.0001	8.8760	0.0643
Return Hungary CDS spread	198.4110	0.0000	162.3460	0.0000	163.5410	0.0000	194.7040	0.0000
Return Ireland CDS spread	118.3080	0.0000	174.0350	0.0000	127.8870	0.0000	197.1870	0.0000
Return Italy CDS spread	28.5280	0.0000	82.9720	0.0000	85.3030	0.0000	101.5910	0.0000
Return Latvia CDS spread	15.7910	0.0001	26.1330	0.0000	17.5790	0.0005	21.8060	0.0002
Return Lithuania CDS spread	28.1220	0.0000	75.1080	0.0000	59.5190	0.0000	53.1040	0.0000
Return Poland CDS spread	76.1730	0.0000	445.3640	0.0000	384.0200	0.0000	263.9630	0.0000
Return Portugal CDS spread	34.0230	0.0000	19.5590	0.0001	237.0150	0.0000	202.5500	0.0000
Return Romania CDS spread	75.7730	0.0000	151.7350	0.0000	149.6430	0.0000	117.9750	0.0000
Return Slovakia CDS spread	51.9980	0.0000	170.1440	0.0000	143.9890	0.0000	170.5650	0.0000
Return Slovenia CDS spread	68.5330	0.0000	98.5940	0.0000	32.3080	0.0000	48.9940	0.0000
Return Spain CDS spread	484.1540	0.0000	528.6010	0.0000	210.9710	0.0000	46.4480	0.0000
Return Sweden CDS spread	170.8590	0.0000	169.7800	0.0000	60.5140	0.0000	95.3410	0.0000
Return UK CDS spread	139.0750	0.0000	77.6690	0.0000	91.6680	0.0000	67.5130	0.0000

The selected GARCH-class models (GARCH (1,1), EGARCH, GJR-GARCH, APARCH, TGARCH, IGARCH) were applied to all 23 EU countries, as well as the four tests that will assess which GARCH model is the better fit for each country.

Table 5. presents the values for 30 days out-of-sample period. GARCH (1,1) was the most appropriate model regarding sovereign CDS forecasting for Bulgaria, Croatia, Cyprus, Estonia; EGARCH fitted the best the Romanian sovereign CDS; GJR-GARCH resulted as the best for Belgium, Ireland, Poland, Portugal, Slovakia, Spain and Sweden; APARCH forecasted the best the CDS from Czech Republic, Denmark, Italy and Slovenia; TGARCH was not the most appropriate model for any country and IGARCH is the most appropriate model Austria, France, Germany, Hungary, Lithuania and UK.

As we can observe, for some specific countries and some specific models (Belgium – EGARCH, Estonia – APARCH, etc.) and even for all model in the case of Latvia, it appears FLL which means flat log-likelihood encountered, an error message that appeared in my econometrics program while testing the models. Econometrics software often uses the maximum likelihood method to estimate the parameters of a model. Behind this method is an optimization function (seeks to maximize the likelihood function of your model). If the maximization process does not achieve the desired results, it will give an error. In this case, the likelihood function does not reach the maximum but falls into a flat area, so the optimization function stops and reports this error.

As a conclusion for the 30 days out-of-sample period forecasting performance, the GJR-GARCH is the best fit for most countries (7 countries), followed closely by IGARCH model (6 countries) and GARCH (1,1) and APARCH, both for the 4 countries and EGARCH for 1 country.

Table 5. 30 days out-of-sample results

Out-of-Sample 30 days CEE	GARCH (1,1)				EGARCH				GJR-GARCH				APARCH				TGARCH				IGARCH			
Variable	LL	AIC	HQIC	SBIC	LL	AIC	HQIC	SBIC	LL	AIC	HQIC	SBIC	LL	AIC	HQIC	SBIC	LL	AIC	HQIC	SBIC	LL	AIC	HQIC	SBIC
Return Austria CDS spread	33.4013	-20.9342	-22.1422	-21.5351	FLL	FLL	FLL	FLL	35.5202	-22.3468	-23.5547	-22.9477	FLL	FLL	FLL	FLL	35.5202	-22.3468	-23.5547	-22.9477	**37.2058**	**-23.4705**	**-24.6785**	**-24.0715**
Return Belgium CDS spread	33.5558	-21.0372	-22.2452	-21.6382	28.2751	-17.5167	-18.7247	-18.1176	**33.6883**	**-21.1255**	**-22.3335**	**-21.7265**	43.7326	-27.8218	-29.0297	-28.4227	24.7393	-15.8262	-16.4301	-16.1266	33.4081	-20.9388	-22.1467	-21.5397
Return Bulgaria CDS spread	**39.5264**	**-25.0176**	**-26.2255**	**-25.6185**	32.5812	-20.3875	-21.5954	-20.9884	39.3168	-24.8778	-26.0858*	-25.4788	37.6693	-23.7796	-24.9875	-24.3805	39.1901	-25.4600	-26.0640	-25.7605	38.4462	-24.2975	-25.5054	-24.8984
Return Croatia CDS spread	**45.8204**	**-29.2136**	**-30.4215**	**-29.8145**	37.5145	-23.6764	-24.8843	-24.2773	45.6869	-29.1246	-30.3325	-29.7255	40.4800	-25.6533	-26.8613	-26.2543	37.6951	-24.4634	-25.0674	-24.7639	45.8012	-29.2008	-30.4088	-29.8018
Return Cyprus CDS spread	**29.8800**	**-18.5867**	**-19.7946**	**-19.1876**	FLL	FLL	FLL	FLL	26.2723	-16.1815	-17.3895	-16.7825	24.1606	-14.7737	-15.9816	-15.3746	25.7960	-16.5307	-17.1347	-16.8311	27.4754	-16.9836	-18.1915	-17.5845
Return Czech Republic CDS spread	40.4489	-25.6326	-26.8405	-26.2335	32.3742	-20.2495	-21.4574	-20.8504	42.4623	-26.9749	-28.1828	-27.5758	**43.0751**	**-27.3834**	**-28.5913**	**-27.9843**	31.2950	-20.1967	-20.8007	-20.4972	42.0756	-26.7170	-27.9250	-27.3180
Return Denmark CDS spread	24.2352	-14.8234	-16.0314	-15.4244	21.4767	-12.9845	-14.1924	-13.5854	25.0732	-15.3821	-16.5901	-15.9830	**39.0591**	**-24.7060**	**-25.9140**	**-25.3070**	25.0251	-16.0168	-16.6207	-16.3172	25.2496	-15.4998	-16.7077	-16.1007
Return Estonia CDS spread	**61.8449**	**-39.8966**	**-41.1046**	**-40.4975**	FLL	FLL	FLL	FLL	48.1872	-30.7914	-31.9994	-31.3924	FLL	FLL	FLL	FLL	41.4498	-26.9665	-27.5705	-27.2670	47.2146	-30.1431	-31.3510	-30.7440
Return France CDS spread	30.5688	-19.0458	-20.2538	-19.6468	29.6771	-18.4514	-19.6593	-19.0523	30.7375	-19.1583	-20.3663	-19.7593	29.6001	-18.4001	-19.6080	-19.0010	23.2428	-14.8286	-15.4325	-15.1290	**30.9942**	**-19.3295**	**-20.5374**	**-19.9304**
Return Germany CDS spread	24.5443	-15.0296	-16.2375	-15.6305	21.3787	-12.9191	-14.1271	-13.5201	25.4142	-15.6095	-16.8174	-16.2104	24.5443	-15.0296	-16.2375	-15.6305	25.4142	-15.6095	-16.8174	-16.2104	**26.1916**	**-16.1278**	**-17.3357**	**-16.7287**
Return Hungary CDS spread	52.2210	-33.4807	-34.6886	-34.0816	43.4109	-27.6073	-28.8152	-28.2082	52.2944	-33.5296	-34.7375	-34.1305	FLL	FLL	FLL	FLL	40.8125	-26.5417	-27.1456	-26.8421	**52.8542**	**-33.9028**	**-35.1107**	**-34.5037**
Return Ireland CDS spread	27.4851	-16.9901	-18.1980	-17.5910	25.7345	-15.8230	-17.0309	-16.4239	**27.7877**	**-17.1918**	**-18.3997**	**-17.7927**	26.4366	-16.2910	-17.4990	-16.8920	22.9419	-14.6279	-15.2319	-14.9284	26.4603	-16.3069	-17.5148	-16.9078
Return Italy CDS spread	31.3094	-19.5396	-20.7476	-20.1405	29.2495	-18.1663	-19.3743	-18.7673	32.5820	-20.3880	-21.5959	-20.9889	**36.0529**	**-22.7020**	**-23.9099**	**-23.3029**	32.5820	-20.3880	-21.5959	-20.9889	30.9778	-19.3186	-20.5265	-19.9195
Return Latvia CDS spread	FLL	FLL	FLL	FLL	FLL	FLL	FLL	FLL	FLL	FLL	FLL	FLL	FLL	FLL	FLL	FLL	FLL	FLL	FLL	FLL	FLL	FLL	FLL	FLL
Return Lithuania CDS spread	41.2797	-26.1865	-27.3944	-26.7874	32.6767	-20.4511	-21.6590	-21.0520	39.7118	-25.1412	-26.3491	-25.7421	37.2977	-23.5318	-24.7397	-24.1327	29.9198	-19.2799	-19.8838	-19.5803	**42.2819**	**-26.8546**	**-28.0625**	**-27.4555**
Return Poland CDS spread	40.2817	-25.5212	-26.7291	-26.1221	32.9084	-20.6056	-21.8135	-21.2065	**40.3719**	**-25.5812**	**-26.7892**	**-26.1822**	34.9740	-21.9826	-23.1906	-22.5836	36.7865	-23.8577	-24.4617	-24.1582	40.0348	-25.3565	-26.5645	-25.9574
Return Portugal CDS spread	44.7662	-28.5108	-29.7187	-29.1117	35.1328	-22.0885	-23.2964	-22.6894	**44.7889**	**-28.5260**	**-29.7339**	**-29.1269**	29.8602	-18.5735	-19.7814	-19.1744	26.1128	-16.7419	-17.3458	-17.0423	44.7344	-28.4896	-29.6975	-29.0905
Return Romania CDS spread	37.0587	-23.3725	-24.5804	-23.9734	**40.6013**	**-25.7342**	**-26.9421**	**-26.3351**	37.5133	-23.6755	-24.8835	-24.2764	FLL	FLL	FLL	FLL	32.1674	-20.7783	-21.3822	-21.0787	37.1803	-23.4535	-24.6615	-24.0545
Return Slovakia CDS spread	41.2173	-26.1448	-27.3528	-26.7458	33.9159	-21.2772	-22.4852	-21.8782	**41.4090**	**-26.2727**	**-27.4806**	**-26.8736**	41.1897	-26.1265	-27.3344	-26.7274	38.4910	-24.9940	-25.5979	-25.2944	39.0675	-25.3784	-25.9823	-25.6788
Return Slovenia CDS spread	48.4473	-30.9649	-32.1728	-31.5658	41.1210	-26.0807	-27.2886	-26.6816	48.8392	-31.2261	-32.4341	-31.8271	**51.4695**	**-32.9797**	**-34.1876**	**-33.5806**	40.5681	-26.3787	-26.9827	-26.6792	49.1530	-31.4354	-32.6433	-32.0363
Return Spain CDS spread	27.2495	-16.8330	-18.0409	-17.4339	26.7064	-16.4709	-17.6789	-17.0719	**28.6954**	**-17.7970**	**-19.0049**	**-18.3979**	26.9073	-16.6049	-17.8128	-17.2058	26.3262	-16.8841	-17.4881	-17.1846	27.5798	-17.0532	-18.2611	-17.6541
Return Sweden CDS spread	35.4249	-22.2833	-23.4912	-22.8842	27.5140	-17.0093	-18.2173	-17.6103	**36.3753**	**-22.9169**	**-24.1248**	**-23.5178**	FLL	FLL	FLL	FLL	36.3067	-23.5378	-24.1418	-23.8383	36.2982	-22.8654	-24.0734	-23.4664
Return UK CDS spread	39.5396	-25.0264	-26.2343	-25.6273	FLL	FLL	FLL	FLL	34.5562	-21.7041	-22.9121	-22.3051	31.7018	-19.8012	-21.0091	-20.4021	15.2902	-9.5268	-10.1308	-9.8273	**40.1744**	**-25.4496**	**-26.6575**	**-26.0505**

Table 6. presents the results for the 90 days out-of-sample period regarding forecasting sovereign CDS. For Bulgaria, Croatia, Czech Republic, Estonia, Poland and Portugal, the most appropriate model is GARCH(1,1); for Ireland, Italy and Latvia is EGARCG model; GJR-GARCH is the best model for Austria, France, Lithuania and UK; APARCH and TGARCH were the most appropriate models for two countries: Belgium and Denmark and, respectively, Cyprus and Hungary; for Germany, Romania, Slovakia, Slovenia, Spain and Sweden the most fit model is IGARCH. Similar to the case of 30 days out-of-sample results, there were particular countries on which I couldn't test specific models due to the log likelihood error (FLL).

The conclusion for this out-of-sample period is that IGARCH model was the most appropriate model in the case of 6 countries, GARCH (1,1) also for 6 countries; GJR-GARCH is the choice for 4 countries, EGARCH for 3 countries and APARCH and TGARCH for 2 countries.

Table 6. 90 days out-of-sample results

Out-of-Sample 90 days	GARCH (1,1)				EGARCH				GJR-GARCH				APARCH				TGARCH				IGARCH			
Variable	LL	AIC	HQIC	SBIC	LL	AIC	HQIC	SBIC	LL	AIC	HQIC	SBIC	LL	AIC	HQIC	SBIC	LL	AIC	HQIC	SBIC	LL	AIC	HQIC	SBIC
Return Austria CDS spread	102.1190	-16.6865	-16.7164	-16.6057	FLL	FLL	FLL	FLL	**104.6010**	**-17.1001**	**-17.1300**	**-17.0193**	FLL	FLL	FLL	FLL	70.1877	-11.5313	-11.5462	-11.4909	96.1415	-15.6903	-15.7202	-15.6094
Return Belgium CDS spread	93.8397	-14.9733	-15.0331	-14.8116	73.7354	11.6226	-11.6824	-11.4609	96.1145	-15.3524	-15.4123	-15.1908	**139.3580**	**-22.5596**	**-22.6195**	**-22.3980**	72.8063	-11.6344	-11.6793	-11.5132	93.2697	-14.8783	-14.9381	-14.7166
Return Bulgaria CDS spread	**159.1050**	**-26.0175**	**-26.0624**	**-25.8963**	129.8210	-21.3732	-21.4181	-21.2520	158.2560	-25.8760	-25.9209	-25.7548	145.9100	-23.8184	-23.8633	-23.6972	158.7360	-25.7893	-25.8492	-25.6277	154.9980	-25.3330	-25.3779	-25.2118
Return Croatia CDS spread	**145.3350**	**-23.8891**	**-23.9190**	**-23.8083**	134.4630	-22.0772	-22.1071	-21.9964	144.8230	-23.8038	-23.8337	-23.7230	138.6590	-22.7765	-22.8064	-22.6957	145.0150	-23.6691	-23.7140	-23.5479	143.3170	-23.5529	-23.5828	-23.4721
Return Cyprus CDS spread	81.4984	-13.4164	-13.4314	-13.3760	FLL	FLL	FLL	FLL	88.6722	-14.6120	-14.6270	-14.5716	85.6774	-13.9462	-13.9762	-13.8654	**89.2606**	**-14.3768**	**-14.4216**	**-14.2555**	84.2839	-13.7140	-13.7439	-13.6332
Return Czech Republic CDS spread	**128.9470**	**-21.1578**	**-21.1877**	**-21.0770**	116.7430	-19.1302	-19.1751	-19.0429	127.8850	-20.9809	-21.0108	-20.9001	126.2700	-20.7117	-20.7416	-20.6308	127.9040	-20.8174	-20.8623	-20.6962	128.8720	-21.1453	-21.1753	-21.0645
Return Denmark CDS spread	67.2460	-10.7077	-10.7525	-10.5864	71.3966	-11.3994	-11.4443	-11.2782	69.8143	-11.3350	-11.3799	-11.2216	**75.6430**	**-12.2738**	**-12.3038**	**-12.1930**	71.0102	-11.3350	-11.3799	-11.2138	70.6990	-11.4498	-11.4797	-11.3690
Return Estonia CDS spread	**185.6510**	**-30.6085**	**-30.6384**	**-30.5277**	FLL	FLL	FLL	FLL	183.1420	-30.1903	-30.2202	-30.1095	FLL	FLL	FLL	FLL	183.6400	-30.1066	-30.1515	-29.9854	181.7420	-29.9569	-29.9869	-29.8761
Return France CDS spread	94.6300	-15.4383	-15.4683	-15.3575	88.8270	-14.5308	-14.5906	-14.3004	**95.3783**	**-15.5631**	**-15.6143**	**-15.4822**	93.7277	-15.2879	-15.3179	-15.2071	74.3729	-12.2288	-12.2438	-12.1884	95.3582	-15.5597	-15.5896	-15.4789
Return Germany CDS spread	88.5534	-14.2589	-14.3056	-14.1137	81.0837	-13.0144	-13.0742	-12.8927	87.3341	-14.0557	-14.1107	-13.9345	86.0827	-13.8668	-13.9266	-13.7259	88.3050	-14.0508	-14.1107	-13.8892	**93.9036**	**-15.1508**	**-15.2107**	**-15.0294**
Return Hungary CDS spread	161.0640	-26.5106	-26.5405	-26.4298	133.7040	-21.9506	-21.9805	-21.8698	161.3350	-26.5558	-26.5857	-26.4750	FLL	FLL	FLL	FLL	**161.6700**	**-26.4451**	**-26.4900**	**-26.3238**	156.6860	-25.7810	-25.8109	-25.7002
Return Ireland CDS spread	93.6846	-15.2808	-15.3107	-15.2000	**95.7515**	**-15.6253**	**-15.6552**	**-15.5444**	92.5207	-15.0868	-15.1167	-15.0060	95.2773	-15.5462	-15.5761	-15.4654	92.5995	-14.9332	-14.9781	-14.8120	92.8977	-15.1496	-15.1795	-15.0688
Return Italy CDS spread	85.8553	-13.9759	-14.0058	-13.8951	**87.0101**	**-14.1684**	**-14.1983**	**-14.0875**	82.4682	-13.4114	-13.4413	-13.3305	85.8287	-13.9715	-14.0014	-13.8906	82.4734	-13.2456	-13.2905	-13.1243	84.5283	-13.7547	-13.7846	-13.6739
Return Latvia CDS spread	488.6030	-80.9338	-80.9787	-80.8125	**499.6200**	**-82.7700**	**-82.8149**	**-82.6488**	FLL	FLL	FLL	FLL	496.8380	-82.3063	-82.3512	-82.1851	FLL	FLL	FLL	FLL	496.8670	-82.3111	-82.3560	-82.1899
Return Lithuania CDS spread	132.1120	-21.6853	-21.7153	-21.6045	129.9870	-21.1645	-21.2094	-21.0433	**143.1080**	**-23.5180**	**-23.5522**	**-23.4371**	135.3450	-22.0575	-22.1023	-21.9362	91.1968	-15.0328	-15.0478	-14.9924	138.6770	-22.7794	-22.8094	-22.6986
Return Poland CDS spread	**145.8450**	**-23.9742**	**-24.0041**	**-23.8934**	126.2220	-20.5371	-20.5820	-20.4525	145.6790	-23.9464	-23.9763	-23.8656	128.1430	-21.0239	-21.0538	-20.9430	145.6800	-23.7800	-23.8249	-23.6588	145.1470	-23.8579	-23.8878	-23.7771
Return Portugal CDS spread	**99.5542**	**-16.2590**	**-16.2889**	**-16.1782**	95.1180	-15.3530	-15.3979	-15.2318	99.3965	-16.2328	-16.2627	-16.1519	93.7744	-15.2957	-15.3257	-15.2149	77.0786	-12.6798	-12.6947	-12.6394	99.3890	-16.2315	-16.2614	-16.1507
Return Romania CDS spread	122.6050	-20.1008	-20.1308	-20.0200	117.4600	-19.2433	-19.2732	-19.1625	121.6300	-19.9383	-19.9683	-19.8575	FLL	FLL	FLL	FLL	121.6300	-19.7717	-19.8166	-19.6505	**124.0860**	**-20.3477**	**-20.3776**	**-20.2669**
Return Slovakia CDS spread	157.1590	-25.6932	-25.7381	-25.5720	136.4620	-22.0771	-22.1369	-21.9154	156.7380	-25.6230	-25.6679	-25.5018	154.0320	-25.1720	-25.2169	-25.0508	152.3470	-25.0578	-25.0877	-24.9769	**157.8660**	**-25.8110**	**-25.8558**	**-25.6897**
Return Slovenia CDS spread	154.4630	-25.4105	-25.4404	-25.3296	125.7420	-20.6237	-20.6537	-20.5429	153.5430	-25.2572	-25.2871	-25.1764	155.8460	-25.6409	-25.6709	-25.5601	153.5600	-25.0934	-25.1383	-24.9721	**155.6160**	**-25.6027**	**-25.6326**	**-25.5218**
Return Spain CDS spread	110.5120	-17.9186	-17.9635	-17.7974	104.1010	-16.8501	-16.8950	-16.7289	111.5840	-18.0974	-18.1423	-17.9762	103.4290	-16.7382	16.7831	-16.6169	112.0530	-18.0088	-18.0686	-17.8471	**112.4100**	**-18.2349**	**-18.2798**	**-18.1137**
Return Sweden CDS spread	51.1820	-8.1970	-8.2269	-8.1162	43.6721	-7.0839	-7.0988	-7.0434	47.6458	-7.6076	-7.6376	-7.5268	48.6914	-7.7819	-7.8118	-7.7011	47.6674	-7.4446	-7.4895	-7.3234	**52.9792**	**-8.4965**	**-8.5265**	**-8.4157**
Return UK CDS spread	101.6270	16.2712	-16.3310	-16.1095	FLL	FLL	FLL	FLL	**107.1680**	**-17.1946**	**-17.2545**	**-17.0330**	98.1115	-15.6853	-15.7451	-15.5236	102.8240	-16.6374	-16.6823	-16.5162	102.7840	-16.7810	-16.8408	-16.6193

In Table 7. there are the results for the 180 days out-of-sample period. GARCH (1,1) is the most appropriate model for Bulgaria, Croatia, Czech Republic, Estonia, Hungary, Latvia, Poland and Slovakia; EGARCH is the best model for France, Italy and Spain; GJR-GARCH resulted the best fit for two countries: Austria and Lithuania. The APARCH model is the most appropriate for forecasting sovereign CDS volatility for Belgium, Cyprus, Denmark, Ireland, Portugal and UK; TGARCH wasn't the best choice for any country and IGARCH fitted Germany, Romania, Slovenia and Sweden.

Similar to the case of 30 days out-of-sample results and 90 days out-of-sample results, there were particular countries on which I couldn't test specific models due to the log likelihood error (FLL).

The conclusion for 180 days out-of-sample period is that GARCH (1,1) model was the most appropriate model in the case of 8 countries, followed by APARCH in the case of 6 countries; IGARCH is the choice for 4 countries, EGARCH for 3 countries, GJR-GARCH for 2 countries and TGARCH for no country.

Table 7. 180 days out-of-sample results

Out-of-Sample 180 days	GARCH (1,1)				EGARCH				GJR-GARCH				APARCH				TGARCH				IGARCH			
Variable	LL	AIC	HQIC	SBIC	LL	AIC	HQIC	SBIC	LL	AIC	HQIC	SBIC	LL	AIC	HQIC	SBIC	LL	AIC	HQIC	SBIC	LL	AIC	HQIC	SBIC
Return Austria CDS spread	187.8580	-14.7886	-14.7480	-14.6423	FLL	FLL	FLL	FLL	**198.0260**	**-15.6021**	**-15.5615**	**-15.4558**	FLL	FLL	FLL	FLL	189.0150	-14.9612	-14.9341	-14.8637	175.9840	-13.8387	-13.7982	-13.6925
Return Belgium CDS spread	161.4510	-12.5961	-12.5420	-12.4011	150.3060	11.8644	-11.8374	-11.7669	163.4260	-12.7541	-12.7000	-12.5591	**190.8610**	**-14.9489**	**-14.8948**	**-14.7539**	157.8020	-12.3841	-12.3436	-12.2379	160.2950	-12.5036	-12.4495	-12.3085
Return Bulgaria CDS spread	**330.6870**	**-26.1664**	**-26.1258**	**-26.0201**	275.1380	-21.7710	-21.7305	-21.6248	328.2530	-26.0203	-25.9797	-25.8740	301.6450	-23.8916	-23.8510	-23.7453	322.8710	-25.6697	-25.6426	-25.5722	321.6340	-25.4907	-25.4501	-25.3444
Return Croatia CDS spread	**286.0800**	**-22.7264**	**-22.6994**	**-22.6289**	271.7580	-21.5006	-21.4600	-21.3543	284.8310	-22.6265	-22.5994	-22.5290	278.7280	-22.0582	-22.0176	-21.9120	284.8790	-22.5503	-22.5098	-22.4041	281.3880	-22.3510	-22.3240	-22.2535
Return Cyprus CDS spread	107.9620	-8.4769	-8.4499	-8.3794	FLL	FLL	FLL	FLL	122.7370	-9.6590	-9.6319	-9.5615	**126.6090**	**-9.9687**	**-9.9417**	**-9.8712**	103.1410	-8.1713	-8.1578	-8.1225	111.9270	-8.7942	-8.7671	-8.6967
Return Czech Republic CDS spread	**274.9490**	**-21.8359**	**-21.8089**	**-21.7384**	249.9420	-19.8354	-19.8083	-19.7379	273.6190	-21.7295	-21.7025	-21.6320	270.4870	-21.4790	-21.4519	-21.3815	273.6560	-21.6525	-21.6119	-21.5062	274.8660	-21.8293	-21.8022	-21.7318
Return Denmark CDS spread	135.0750	-10.6460	-10.6190	-10.5485	138.3020	-10.9042	-10.8771	-10.8067	141.6080	-11.1687	-11.1416	-11.0712	**152.2880**	**-12.0231**	**-11.9960**	**-11.9256**	141.7500	-11.1000	-11.0595	-10.9538	144.1490	-11.3719	-11.3449	-11.2744
Return Estonia CDS spread	**352.6390**	**-27.8911**	**-27.8370**	**-27.6961**	FLL	FLL	FLL	FLL	349.5640	-27.6451	-27.5910	-27.4948	FLL	FLL	FLL	FLL	347.3930	-27.5514	-27.5109	-27.4052	349.4520	-27.7696	-27.7155	-27.5746
Return France CDS spread	139.8080	-10.8646	-10.8105	10.6696	**145.7410**	**-11.3393**	**-11.2852**	**-11.1442**	141.4490	-10.9959	-10.9418	-10.8009	140.1870	-10.8950	-10.8409	-10.6999	139.4530	-10.9163	-10.8757	-10.7700	141.4230	-10.9939	-10.9398	-10.7988
Return Germany CDS spread	163.3740	-12.8299	-12.7894	-12.6837	158.3630	-12.4291	-12.3885	-12.2828	165.9300	-13.0344	-12.9938	-12.8881	165.1370	-12.9710	-12.9304	-12.8247	156.8610	-12.3889	-12.3619	-12.2914	**174.1670**	**-13.6934**	**-13.6528**	**-13.5471**
Return Hungary CDS spread	**277.9910**	**-21.9993**	**-21.9587**	**-21.8530**	249.0680	-19.6854	-19.6448	-19.5391	277.8340	-21.9867	-21.9462	-21.8405	FLL	FLL	FLL	FLL	275.4270	-21.8742	-21.8471	-21.7767	271.6650	-21.4932	-21.4526	-21.3469
Return Ireland CDS spread	150.9580	-11.7566	-11.7207	-11.6502	155.9050	-12.3154	-12.2853	-12.2149	148.4240	-11.5539	-11.5228	-11.4784	**162.6810**	**-12.8545**	**-12.8274**	**-12.7570**	146.3740	-11.5499	-11.5228	-11.4524	149.4070	-11.6550	-11.6415	-11.6063
Return Italy CDS spread	180.9830	-14.3187	-14.2916	-14.2212	**186.5560**	**-14.6845**	**-14.6439**	**-14.5382**	177.8250	-14.0828	-14.0422	-12.9685	184.4520	-14.6426	-14.6020	-14.4986	179.0350	-14.0828	-14.0422	-13.9365	178.2050	-14.0964	-14.0693	13.9989
Return Latvia CDS spread	**368.6950**	**-29.3356**	**-29.3085**	**-29.2381**	295.4820	-23.4786	-23.4515	-23.3810	FLL	FLL	FLL	FLL	327.4660	-26.0373	-26.0102	-25.9398	FLL	FLL	FLL	FLL	361.3220	-28.7458	-28.7187	-28.6483
Return Lithuania CDS spread	281.7300	-22.2984	-22.2579	-22.1522	238.6040	-18.8483	-18.8078	-18.7021	**305.0090**	**-24.1607**	**-24.1201**	**-24.0144**	226.6400	-17.8912	-17.8507	-17.7450	267.3080	-21.2247	-21.1976	-21.1271	295.5100	-23.4008	-23.3602	-23.2545
Return Poland CDS spread	**257.6730**	**-20.4539**	**-20.4268**	**-20.3563**	237.6730	-18.8539	-18.8268	-18.7564	256.9850	-20.3988	-20.3718	-20.3013	238.7590	-18.9407	-18.9137	-18.8432	257.0250	-20.3220	-20.2814	-20.1757	256.5380	-20.3630	-20.3360	-20.2655
Return Portugal CDS spread	148.6130	-11.7290	-11.7020	-11.6315	159.3440	-12.5875	-12.5605	-12.4900	149.2550	-11.7804	-11.7534	-11.6829	**162.0410**	**-12.8033**	**-12.7762**	**-12.7058**	149.3420	-11.7074	-11.6668	-11.5611	148.1400	-11.6912	-11.6641	-11.5937
Return Romania CDS spread	184.7580	-14.5406	-14.5001	-14.3944	161.3770	-12.6702	-12.6296	-12.5239	180.0190	-14.1615	-14.1210	-14.0153	FLL	FLL	FLL	FLL	180.0600	-14.0848	-14.0307	-13.8898	**187.9340**	**-14.7947**	**-14.7541**	**-14.6484**
Return Slovakia CDS spread	**272.9970**	**-21.6797**	**-21.6527**	**-21.5822**	248.4220	-19.6338	-19.5932	-19.4875	271.1770	-21.5342	-21.5071	-21.4367	269.6880	-21.4151	-21.3880	-21.3175	271.4980	-21.4798	-21.4392	-21.3335	272.5370	-21.6429	-21.6159	-21.5454
Return Slovenia CDS spread	313.9560	-24.9565	-24.9295	-24.8590	261.8360	-20.7869	-20.7599	-20.6894	312.1020	-24.8082	-24.7811	-24.7107	315.2550	-25.0604	-25.0333	-24.9629	312.1170	-24.7293	-24.6888	-24.5831	**316.0850**	**-25.1268**	**-25.0998**	**-25.0293**
Return Spain CDS spread	126.0420	-9.9234	-9.8964	-9.8259	**148.6220**	**-11.7297**	**-11.7027**	**-11.6322**	138.5230	-10.9219	-10.8948	-10.8243	148.1710	-11.6937	-11.6666	-11.5962	139.0100	-10.8808	-10.8402	-10.7345	129.3350	-10.1868	-10.1598	-10.0893
Return Sweden CDS spread	107.6390	-8.5400	-8.4859	-8.3747	98.3516	-7.7081	-7.6811	-7.6106	106.3200	-8.3456	-8.3185	-8.2481	109.2170	-8.5773	-8.5503	-8.4798	106.7740	-8.3019	-8.2613	-8.1556	**111.4250**	**-8.8376**	**-8.7835**	**-8.6426**
Return UK CDS spread	167.0030	-13.1186	-13.0916	-13.0211	FLL	FLL	FLL	FLL	175.0370	-13.8430	-13.8159	-13.7455	**175.9660**	**-13.9173**	**-13.8903**	**-13.8198**	175.9610	-13.8369	-13.7963	-13.6906	171.5030	-13.6114	-13.5708	-13.4651

Regarding the first hypothesis stated prior the research, that there won't be a single most appropriate GARCH-class model, but there would be different models for certain countries, the results for all three out-of-sample periods show that the hypothesis is accepted. In each of the out-of-sample periods, some countries' sovereign CDS volatility was forecasted better by some models and other countries' CDS volatility by other models. In addition of that, the same country's sovereign CDS volatility had different chosen models according to the forecasted period: for example, Hungary's sovereign CDS volatility was forecasted the best by IGARCH model in the 30 days out-of-sample period, by TGARCH in the 90 days out-of-sample period and by GARCH (1,1) in the 180 days out-of-sample period. There are also countries, for example Bulgaria, for which GARCH (1,1) was the most appropriate model in forecasting sovereign CDS volatility, no matter the out-of-sample period. Table 10 presents the number of countries for each out-of-sample period according to the model it forecasted the sovereign CDS volatility the best.

Table 8. Overview of the GARCH models performance by number of countries

Out-of-sample periods	GARCH (1,1)	EGARCH	GJR-GARCH	APARCH	TGARCH	IGARCH
Out-of-sample 30 days	4	1	7	4	0	6
Out-of-sample 90 days	6	3	4	2	2	6
Out-of-sample 180 days	8	3	2	6	0	4

In order to achieve my second objective and to test the related hypothesis, I have split the countries according to Central-East/West delimitation. Tables 9 and 10 show the results for 30 days out-of-sample period for countries from Central and Eastern Europe and respectively for Western Europe. By analyzing the results, we can observe that the most appropriate model for the majority of the countries in Central and Eastern Europe is GARCH (1,1) for 4 countries, GJR-GARCH, APARCH and IGARCH for 2 countries and TGARCH for no countries. On the other hand, the Western European countries show a more drastic partition: 5 countries had the best results in forecasting sovereign CDS volatility by using GJR-GARCH model, 4 countries by using IGARCH model and 2 countries by using APARCH model. GARCH (1,1), EGARCH and TGARCH weren't the most appropriate model for any of the Western European countries in the 30 day out-of-sample period.

Table 9. 30 days out-of-sample results CEE countries

Out-of-Sample 30 days CEE	GARCH (1,1)				EGARCH				GJR-GARCH				APARCH				TGARCH				IGARCH			
Variable	LL	AIC	HQIC	SBIC	LL	AIC	HQIC	SBIC	LL	AIC	HQIC	SBIC	LL	AIC	HQIC	SBIC	LL	AIC	HQIC	SBIC	LL	AIC	HQIC	SBIC
Return Bulgaria CDS spread	**39.5264**	**-25.0176**	**-26.2255**	**-25.6185**	32.5812	-20.3875	-21.5954	-20.9884	39.3168	-24.8778	-26.0858*	-25.4788	37.6693	-23.7796	-24.9875	-24.3805	39.1901	-25.4600	-26.0640	-25.7605	38.4462	-24.2975	-25.5054	-24.8984
Return Croatia CDS spread	**45.8204**	**-29.2136**	**-30.4215**	**-29.8145**	37.5145	-23.6764	-24.8843	-24.2773	45.6869	-29.1246	-30.3325	-29.7255	40.4800	-25.6533	-26.8613	-26.2543	37.6951	-24.4634	-25.0674	-24.7639	45.8012	-29.2008	-30.4088	-29.8018
Return Cyprus CDS spread	**29.8800**	**-18.5867**	**-19.7946**	**-19.1876**	FLL	FLL	FLL	FLL	26.2723	-16.1815	-17.3895	-16.7825	24.1606	-14.7737	-15.9816	-15.3746	25.7960	-16.5307	-17.1347	-16.8311	27.4754	-16.9836	-18.1915	-17.5845
Return Czech Republic CDS spread	40.4489	-25.6326	-26.8405	-26.2335	32.3742	-20.2495	-21.4574	-20.8504	42.4623	-26.9749	-28.1828	-27.5758	**43.0751**	**-27.3834**	**-28.5913**	**-27.9843**	31.2950	-20.1967	-20.8007	-20.4972	42.0756	-26.7170	-27.9250	-27.3180
Return Estonia CDS spread	**61.8449**	**-39.8966**	**-41.1046**	**-40.4975**	FLL	FLL	FLL	FLL	48.1872	-30.7914	-31.9994	-31.3924	FLL	FLL	FLL	FLL	41.4498	-26.9665	-27.5705	-27.2670	47.2146	-30.1431	-31.3510	-30.7440
Return Hungary CDS spread	52.2210	-33.4807	-34.6886	-34.0816	43.4109	-27.6073	-28.8152	-28.2082	52.2944	-33.5296	-34.7375	-34.1305	FLL	FLL	FLL	FLL	40.8125	-26.5417	-27.1456	-26.8421	**52.8542**	**-33.9028**	**-35.1107**	**-34.5037**
Return Latvia CDS spread	FLL	FLL	FLL	FLL	FLL	FLL	FLL	FLL	FLL	FLL	FLL	FLL	FLL	FLL	FLL	FLL	FLL	FLL	FLL	FLL	FLL	FLL	FLL	FLL
Return Lithuania CDS spread	41.2797	-26.1865	-27.3944	-26.7874	32.6767	-20.4511	-21.6590	-21.0520	39.7118	-25.1412	-26.3491	-25.7421	37.2977	-23.5318	-24.7397	-24.1327	29.9198	-19.2799	-19.8838	-19.5803	**42.2819**	**-26.8546**	**-28.0625**	**-27.4555**
Return Poland CDS spread	40.2817	-25.5212	-26.7291	-26.1221	32.9084	-20.6056	-21.8135	-21.2065	**40.3719**	**-25.5812**	**-26.7892**	**-26.1822**	34.9740	-21.9826	-23.1906	-22.5836	36.7865	-23.8577	-24.4617	-24.1582	40.0348	-25.3565	-26.5645	-25.9574
Return Romania CDS spread	37.0587	-23.3725	-24.5804	-23.9734	**40.6013**	**-25.7342**	**-26.9421**	**-26.3351**	37.5133	-23.6755	-24.8835	-24.2764	FLL	FLL	FLL	FLL	32.1674	-20.7783	-21.3822	-21.0787	37.1803	-23.4535	-24.6615	-24.0545
Return Slovakia CDS spread	41.2173	-26.1448	-27.3528	-26.7458	33.9159	-21.2772	-22.4852	-21.8782	**41.4090**	**-26.2727**	**-27.4806**	**-26.8736**	41.1897	-26.1265	-27.3344	-26.7274	38.4910	-24.9940	-25.5979	-25.2944	39.0675	-25.3784	-25.9823	-25.6788
Return Slovenia CDS spread	48.4473	-30.9649	-32.1728	-31.5658	41.1210	-26.0807	-27.2886	-26.6816	48.8392	-31.2261	-32.4341	-31.8271	**51.4695**	**-32.9797**	**-34.1876**	**-33.5806**	40.5681	-26.3787	-26.9827	-26.6792	49.1530	-31.4354	-32.6433	-32.0363

Table 10. 30 days out-of-sample results WE countries

Out-of-Sample 30 days WE	GARCH (1,1)				EGARCH				GJR-GARCH				APARCH				TGARCH				IGARCH			
Variable	LL	AIC	HQIC	SBIC	LL	AIC	HQIC	SBIC	LL	AIC	HQIC	SBIC	LL	AIC	HQIC	SBIC	LL	AIC	HQIC	SBIC	LL	AIC	HQIC	SBIC
Return Austria CDS spread	33.4013	-20.9342	-22.1422	-21.5351	FLL	FLL	FLL	FLL	35.5202	-22.3468	-23.5547	-22.9477	FLL	FLL	FLL	FLL	35.5202	-22.3468	-23.5547	-22.9477	**37.2058**	**-23.4705**	**-24.6785**	**-24.0715**
Return Belgium CDS spread	33.5558	-21.0372	-22.2452	-21.6382	28.2751	-17.5167	-18.7247	-18.1176	**33.6883**	**-21.1255**	**-22.3335**	**-21.7265**	43.7326	-27.8218	-29.0297	-28.4227	24.7393	-15.8262	-16.4301	-16.1266	33.4081	-20.9388	-22.1467	-21.5397
Return Denmark CDS spread	24.2352	-14.8234	-16.0314	-15.4244	21.4767	-12.9845	-14.1924	-13.5854	25.0732	-15.3821	-16.5901	-15.9830	**39.0591**	**-24.7060**	**-25.9140**	**-25.3070**	25.0251	-16.0168	-16.6207	-16.3172	25.2496	-15.4998	-16.7077	-16.1007
Return France CDS spread	30.5688	-19.0458	-20.2538	-19.6468	29.6771	-18.4514	-19.6593	-19.0523	30.7375	-19.1583	-20.3663	-19.7593	29.6001	-18.4001	-19.6080	-19.0010	23.2428	-14.8286	-15.4325	-15.1290	**30.9942**	**-19.3295**	**-20.5374**	**-19.9304**
Return Germany CDS spread	24.5443	-15.0296	-16.2375	-15.6305	21.3787	-12.9191	-14.1271	-13.5201	25.4142	-15.6095	-16.8174	-16.2104	24.5443	-15.0296	-16.2375	-15.6305	25.4142	-15.6095	-16.8174	-16.2104	**26.1916**	**-16.1278**	**-17.3357**	**-16.7287**
Return Ireland CDS spread	27.4851	-16.9901	-18.1980	-17.5910	25.7345	-15.8230	-17.0309	-16.4239	**27.7877**	**-17.1918**	**-18.3997**	**-17.7927**	26.4366	-16.2910	-17.4990	-16.8920	22.9419	-14.6279	-15.2319	-14.9284	26.4603	-16.3069	-17.5148	-16.9078
Return Italy CDS spread	31.3094	-19.5396	-20.7476	-20.1405	29.2495	-18.1663	-19.3743	-18.7673	32.5820	-20.3880	-21.5959	-20.9889	**36.0529**	**-22.7020**	**-23.9099**	**-23.3029**	32.5820	-20.3880	-21.5959	-20.9889	30.9778	-19.3186	-20.5265	-19.9195
Return Portugal CDS spread	44.7662	-28.5108	-29.7187	-29.1117	35.1328	-22.0885	-23.2964	-22.6894	**44.7889**	**-28.5260**	**-29.7339**	**-29.1269**	29.8602	-18.5735	-19.7814	-19.1744	26.1128	-16.7419	-17.3458	-17.0423	44.7344	-28.4896	-29.6975	-29.0905
Return Spain CDS spread	27.2495	-16.8330	-18.0409	-17.4339	26.7064	-16.4709	-17.6789	-17.0719	**28.6954**	**-17.7970**	**-19.0049**	**-18.3979**	26.9073	-16.6049	-17.8128	-17.2058	26.3262	-16.8841	-17.4881	-17.1846	27.5798	-17.0532	-18.2611	-17.6541
Return Sweden CDS spread	35.4249	-22.2833	-23.4912	-22.8842	27.5140	-17.0093	-18.2173	-17.6103	**36.3753**	**-22.9169**	**-24.1248**	**-23.5178**	FLL	FLL	FLL	FLL	36.3067	-23.5378	-24.1418	-23.8383	36.2982	-22.8654	-24.0734	-23.4664
Return UK CDS spread	39.5396	-25.0264	-26.2343	-25.6273	FLL	FLL	FLL	FLL	34.5562	-21.7041	-22.9121	-22.3051	31.7018	-19.8012	-21.0091	-20.4021	15.2902	-9.5268	-10.1308	-9.8273	**40.1744**	**-25.4496**	**-26.6575**	**-26.0505**

Tables 11 and 12 present the results for the 90 days out-of-sample period according to the Central-Eastern/Western delimitation. 5 from the Central and Eastern European countries have GARCH (1,1) model as the most appropriate model in forecasting sovereign CDS volatility, 3 countries have IGARCH, 2 countries have TGARCH model, 1 country has EGARCH and 1 country has GJR-GARCH. The Western European countries present a rather balanced view: GJR-GARCH and IGARCH are the best models for 3 countries, APARCH and EGARCH are the most appropriate model for 2 countries and 1 country has as the best fit the GARCH (1,1) model.

Table 11. 90 days out-of-sample results CEE countries

Out-of-Sample 90 days CEE	GARCH (1,1)				EGARCH				GJR-GARCH				APARCH				TGARCH				IGARCH			
Variable	LL	AIC	HQIC	SBIC	LL	AIC	HQIC	SBIC	LL	AIC	HQIC	SBIC	LL	AIC	HQIC	SBIC	LL	AIC	HQIC	SBIC	LL	AIC	HQIC	SBIC
Return Bulgaria CDS spread	**159.1050**	**-26.0175**	**-26.0624**	**-25.8963**	129.8210	-21.3732	-21.4181	-21.2520	158.2560	-25.8760	-25.9209	-25.7548	145.9100	-23.8184	-23.8633	-23.6972	158.7360	-25.7893	-25.8492	-25.6277	154.9980	-25.3330	-25.3779	-25.2118
Return Croatia CDS spread	**145.3350**	**-23.8891**	**-23.9190**	**-23.8083**	134.4630	-22.0772	-22.1071	-21.9964	144.8230	-23.8038	-23.8337	-23.7230	138.6590	-22.7765	-22.8064	-22.6957	145.0150	-23.6691	-23.7140	-23.5479	143.3170	-23.5529	-23.5828	-23.4721
Return Cyprus CDS spread	81.4984	-13.4164	-13.4314	-13.3760	FLL	FLL	FLL	FLL	88.6722	-14.6120	-14.6270	-14.5716	85.6774	-13.9462	-13.9762	-13.8654	**89.2606**	**-14.3768**	**-14.4216**	**-14.2555**	84.2839	-13.7140	-13.7439	-13.6332
Return Czech Republic CDS spread	**128.9470**	**-21.1578**	**-21.1877**	**-21.0770**	116.7430	-19.1302	-19.1751	-19.0429	127.8850	-20.9809	-21.0108	-20.9001	126.2700	-20.7117	-20.7416	-20.6308	127.9040	-20.8174	-20.8623	-20.6962	128.8720	-21.1453	-21.1753	-21.0645
Return Estonia CDS spread	**185.6510**	**-30.6085**	**-30.6384**	**-30.5277**	FLL	FLL	FLL	FLL	183.1420	-30.1903	-30.2202	-30.1095	FLL	FLL	FLL	FLL	183.6400	-30.1066	-30.1515	-29.9854	181.7420	-29.9569	-29.9869	-29.8761
Return Hungary CDS spread	161.0640	-26.5106	-26.5405	-26.4298	133.7040	-21.9506	-21.9805	-21.8698	161.3350	-26.5558	-26.5857	-26.4750	FLL	FLL	FLL	FLL	**161.6700**	**-26.4451**	**-26.4900**	**-26.3238**	156.6860	-25.7810	-25.8109	-25.7002
Return Latvia CDS spread	488.6030	-80.9338	-80.9787	-80.8125	**499.6200**	**-82.7700**	**-82.8149**	**-82.6488**	FLL	FLL	FLL	FLL	496.8380	-82.3063	-82.3512	-82.1851	FLL	FLL	FLL	FLL	496.8670	-82.3111	-82.3560	-82.1899
Return Lithuania CDS spread	132.1120	-21.6853	-21.7153	-21.6045	129.9870	-21.1645	-21.2094	-21.0433	**143.1080**	**-23.5180**	**-23.5522**	**-23.4371**	135.3450	-22.0575	-22.1023	-21.9362	91.1968	-15.0328	-15.0478	-14.9924	138.6770	-22.7794	-22.8094	-22.6986
Return Poland CDS spread	**145.8450**	**-23.9742**	**-24.0041**	**-23.8934**	126.2220	-20.5371	-20.5820	-20.4525	145.6790	-23.9464	-23.9763	-23.8656	128.1430	-21.0239	-21.0538	-20.9430	145.6800	-23.7800	-23.8249	-23.6588	145.1470	-23.8579	-23.8878	-23.7771
Return Romania CDS spread	122.6050	-20.1008	-20.1308	-20.0200	117.4600	-19.2433	-19.2732	-19.1625	121.6300	-19.9383	-19.9683	-19.8575	FLL	FLL	FLL	FLL	121.6300	-19.7717	-19.8166	-19.6505	**124.0860**	**-20.3477**	**-20.3776**	**-20.2669**
Return Slovakia CDS spread	157.1590	-25.6932	-25.7381	-25.5720	136.4620	-22.0771	-22.1369	-21.9154	156.7380	-25.6230	-25.6679	-25.5018	154.0320	-25.1720	-25.2169	-25.0508	152.3470	-25.0578	-25.0877	-24.9769	**157.8660**	**-25.8110**	**-25.8558**	**-25.6897**
Return Slovenia CDS spread	154.4630	-25.4105	-25.4404	-25.3296	125.7420	-20.6237	-20.6537	-20.5429	153.5430	-25.2572	-25.2871	-25.1764	155.8460	-25.6409	-25.6709	-25.5601	153.5600	-25.0934	-25.1383	-24.9721	**155.6160**	**-25.6027**	**-25.6326**	**-25.5218**

Table 12. 90 days out-of-sample results WE countries

Out-of-Sample 90 days WE	GARCH (1,1)				EGARCH				GJR-GARCH				APARCH				TGARCH				IGARCH			
Variable	LL	AIC	HQIC	SBIC	LL	AIC	HQIC	SBIC	LL	AIC	HQIC	SBIC	LL	AIC	HQIC	SBIC	LL	AIC	HQIC	SBIC	LL	AIC	HQIC	SBIC
Return Austria CDS spread	102.1190	-16.6865	-16.7164	-16.6057	FLL	FLL	FLL	FLL	**104.6010**	**-17.1001**	**-17.1300**	**-17.0193**	FLL	FLL	FLL	FLL	70.1877	-11.5313	-11.5462	-11.4909	96.1415	-15.6903	-15.7202	-15.6094
Return Belgium CDS spread	93.8397	-14.9733	-15.0331	-14.8116	73.7354	11.6226	-11.6824	-11.4609	96.1145	-15.3524	-15.4123	-15.1908	**139.3580**	**-22.5596**	**-22.6195**	**-22.3980**	72.8063	-11.6344	-11.6793	-11.5132	93.2697	-14.8783	-14.9381	-14.7166
Return Denmark CDS spread	67.2460	-10.7077	-10.7525	-10.5864	71.3966	-11.3994	-11.4443	-11.2782	69.8143	-11.3350	-11.3799	-11.2216	**75.6430**	**-12.2738**	**-12.3038**	**-12.1930**	71.0102	-11.3350	-11.3799	-11.2138	70.6990	-11.4498	-11.4797	-11.3690
Return France CDS spread	94.6300	-15.4383	-15.4683	-15.3575	88.8270	-14.5308	-14.5906	-14.3004	**95.3783**	**-15.5631**	**-15.6143**	**-15.4822**	93.7277	-15.2879	-15.3179	-15.2071	74.3729	-12.2288	-12.2438	-12.1884	95.3582	-15.5597	-15.5896	-15.4789
Return Germany CDS spread	88.5534	-14.2589	-14.3056	-14.1137	81.0837	-13.0144	-13.0742	-12.8927	87.3341	-14.0557	-14.1107	-13.9345	86.0827	-13.8668	-13.9266	-13.7259	88.3050	-14.0508	-14.1107	-13.8892	**93.9036**	**-15.1508**	**-15.2107**	**-15.0294**
Return Ireland CDS spread	93.6846	-15.2808	-15.3107	-15.2000	**95.7515**	**-15.6253**	**-15.6552**	**-15.5444**	92.5207	-15.0868	-15.1167	-15.0060	95.2773	-15.5462	-15.5761	-15.4654	92.5995	-14.9332	-14.9781	-14.8120	92.8977	-15.1496	-15.1795	-15.0688
Return Italy CDS spread	85.8553	-13.9759	-14.0058	-13.8951	**87.0101**	**-14.1684**	**-14.1983**	**-14.0875**	82.4682	-13.4114	-13.4413	-13.3305	85.8287	-13.9715	-14.0014	-13.8906	82.4734	-13.2456	-13.2905	-13.1243	84.5283	-13.7547	-13.7846	-13.6739
Return Portugal CDS spread	**99.5542**	**-16.2590**	**-16.2889**	**-16.1782**	95.1180	-15.3530	-15.3979	-15.2318	99.3965	-16.2328	-16.2627	-16.1519	93.7744	-15.2957	-15.3257	-15.2149	77.0786	-12.6798	-12.6947	-12.6394	99.3890	-16.2315	-16.2614	-16.1507
Return Spain CDS spread	110.5120	-17.9186	-17.9635	-17.7974	104.1010	-16.8501	-16.8950	-16.7289	111.5840	-18.0974	-18.1423	-17.9762	103.4290	-16.7382	16.7831	-16.6169	112.0530	-18.0088	-18.0686	-17.8471	**112.4100**	**-18.2349**	**-18.2798**	**-18.1137**
Return Sweden CDS spread	51.1820	-8.1970	-8.2269	-8.1162	43.6721	-7.0839	-7.0988	-7.0434	47.6458	-7.6076	-7.6376	-7.5268	48.6914	-7.7819	-7.8118	-7.7011	47.6674	-7.4446	-7.4895	-7.3234	**52.9792**	**-8.4965**	**-8.5265**	**-8.4157**
Return UK CDS spread	101.6270	16.2712	-16.3310	-16.1095	FLL	FLL	FLL	FLL	**107.1680**	**-17.1946**	**-17.2545**	**-17.0330**	98.1115	-15.6853	-15.7451	-15.5236	102.8240	-16.6374	-16.6823	-16.5162	102.7840	-16.7810	-16.8408	-16.6193

The divided results between Central and Eastern and Western European countries for the 180 days out-of-sample period are displayed in Table 13 and 14. The Central and Eastern European countries results show clear that GARCH (1,1) is the most appropriate model for the majority of the states (8), while IGARCH fit 2 countries and GJR-GARCH and APARCH 1 country each. Regarding Western European countries, the results are slightly more balanced: APARCH fit 5 countries, EGARCH fit 3 countries, IGARCH was the best model for 2 countries and GJR-GARCH fit only 1 country.

Table 13. 180 days out-of-sample results CEE countries

Out-of-Sample 180 days CEE	GARCH (1,1)			EGARCH				GJR-GARCH				APARCH				TGARCH				IGARCH			
Variable	AIC	HQIC	SBIC	LL	AIC	HQIC	SBIC	LL	AIC	HQIC	SBIC	LL	AIC	HQIC	SBIC	LL	AIC	HQIC	SBIC	LL	AIC	HQIC	SBIC
Return Bulgaria CDS spread	**-26.1664**	**-26.1258**	**-26.0201**	275.1380	-21.7710	-21.7305	-21.6248	328.2530	-26.0203	-25.9797	-25.8740	301.6450	-23.8916	-23.8510	-23.7453	322.8710	-25.6697	-25.6426	-25.5722	321.6340	-25.4907	-25.4501	-25.3444
Return Croatia CDS spread	**-22.7264**	**-22.6994**	**-22.6289**	271.7580	-21.5006	-21.4600	-21.3543	284.8310	-22.6265	-22.5994	-22.5290	278.7280	-22.0582	-22.0176	-21.9120	284.8790	-22.5503	-22.5098	-22.4041	281.3880	-22.3510	-22.3240	-22.2535
Return Cyprus CDS spread	-8.4769	-8.4499	-8.3794	FLL	FLL	FLL	FLL	122.7370	-9.6590	-9.6319	-9.5615	**126.6090**	**-9.9687**	**-9.9417**	**-9.8712**	103.1410	-8.1713	-8.1578	-8.1225	111.9270	-8.7942	-8.7671	-8.6967
Return Czech Republic CDS spread	**-21.8359**	**-21.8089**	**-21.7384**	249.9420	-19.8354	-19.8083	-19.7379	273.6190	-21.7295	-21.7025	-21.6320	270.4870	-21.4790	-21.4519	-21.3815	273.6560	-21.6525	-21.6119	-21.5062	274.8660	-21.8293	-21.8022	-21.7318
Return Estonia CDS spread	**-27.8911**	**-27.8370**	**-27.6961**	FLL	FLL	FLL	FLL	349.5640	-27.6451	-27.5910	-27.4948	FLL	FLL	FLL	FLL	347.3930	-27.5514	-27.5109	-27.4052	349.4520	-27.7696	-27.7155	-27.5746
Return Hungary CDS spread	**-21.9993**	**-21.9587**	**-21.8530**	249.0680	-19.6854	-19.6448	-19.5391	277.8340	-21.9867	-21.9462	-21.8405	FLL	FLL	FLL	FLL	275.4270	-21.8742	-21.8471	-21.7767	271.6650	-21.4932	-21.4526	-21.3469
Return Latvia CDS spread	**-29.3356**	**-29.3085**	**-29.2381**	295.4820	-23.4786	-23.4515	-23.3810	FLL	FLL	FLL	FLL	327.4660	-26.0373	-26.0102	-25.9398	FLL	FLL	FLL	FLL	361.3220	-28.7458	-28.7187	-28.6483
Return Lithuania CDS spread	-22.2984	-22.2579	-22.1522	238.6040	-18.8483	-18.8078	-18.7021	**305.0090**	**-24.1607**	**-24.1201**	**-24.0144**	226.6400	-17.8912	-17.8507	-17.7450	267.3080	-21.2247	-21.1976	-21.1271	295.5100	-23.4008	-23.3602	-23.2545
Return Poland CDS spread	**-20.4539**	**-20.4268**	**-20.3563**	237.6730	-18.8539	-18.8268	-18.7564	256.9850	-20.3988	-20.3718	-20.3013	238.7590	-18.9407	-18.9137	-18.8432	257.0250	-20.3220	-20.2814	-20.1757	256.5380	-20.3630	-20.3360	-20.2655
Return Romania CDS spread	-14.5406	-14.5001	-14.3944	161.3770	-12.6702	-12.6296	-12.5239	180.0190	-14.1615	-14.1210	-14.0153	FLL	FLL	FLL	FLL	180.0600	-14.0848	-14.0307	-13.8898	**187.9340**	**-14.7947**	**-14.7541**	**-14.6484**
Return Slovakia CDS spread	**-21.6797**	**-21.6527**	**-21.5822**	248.4220	-19.6338	-19.5932	-19.4875	271.1770	-21.5342	-21.5071	-21.4367	269.6880	-21.4151	-21.3880	-21.3175	271.4980	-21.4798	-21.4392	-21.3335	272.5370	-21.6429	-21.6159	-21.5454
Return Slovenia CDS spread	-24.9565	-24.9295	-24.8590	261.8360	-20.7869	-20.7599	-20.6894	312.1020	-24.8082	-24.7811	-24.7107	315.2550	-25.0604	-25.0333	-24.9629	312.1170	-24.7293	-24.6888	-24.5831	**316.0850**	**-25.1268**	**-25.0998**	**-25.0293**

Table 14. 180 days out-of-sample results WE countries

Out-of-Sample 180 days WE	GARCH (1,1)			EGARCH				GJR-GARCH				APARCH				TGARCH				IGARCH			
Variable	AIC	HQIC	SBIC	LL	AIC	HQIC	SBIC	LL	AIC	HQIC	SBIC	LL	AIC	HQIC	SBIC	LL	AIC	HQIC	SBIC	LL	AIC	HQIC	SBIC
Return Austria CDS spread	-14.7886	-14.7480	-14.6423	FLL	FLL	FLL	FLL	**198.0260**	**-15.6021**	**-15.5615**	**-15.4558**	FLL	FLL	FLL	FLL	189.0150	-14.9612	-14.9341	-14.8637	175.9840	-13.8387	-13.7982	-13.6925
Return Belgium CDS spread	-12.5961	-12.5420	-12.4011	150.3060	11.8644	-11.8374	-11.7669	163.4260	-12.7541	-12.7000	-12.5591	**190.8610**	**-14.9489**	**-14.8948**	**-14.7539**	157.8020	-12.3841	-12.3436	-12.2379	160.2950	-12.5036	-12.4495	-12.3085
Return Denmark CDS spread	-10.6460	-10.6190	-10.5485	138.3020	-10.9042	-10.8771	-10.8067	141.6080	-11.1687	-11.1416	-11.0712	**152.2880**	**-12.0231**	**-11.9960**	**-11.9256**	141.7500	-11.1000	-11.0595	-10.9538	144.1490	-11.3719	-11.3449	-11.2744
Return France CDS spread	-10.8646	-10.8105	10.6696	**145.7410**	**-11.3393**	**-11.2852**	**-11.1442**	141.4490	-10.9959	-10.9418	-10.8009	140.1870	-10.8950	-10.8409	-10.6999	139.4530	-10.9163	-10.8757	-10.7700	141.4230	-10.9939	-10.9398	-10.7988
Return Germany CDS spread	-12.8299	-12.7894	-12.6837	158.3630	-12.4291	-12.3885	-12.2828	165.9300	-13.0344	-12.9938	-12.8881	165.1370	-12.9710	-12.9304	-12.8247	156.8610	-12.3889	-12.3619	-12.2914	**174.1670**	**-13.6934**	**-13.6528**	**-13.5471**
Return Ireland CDS spread	-11.7566	-11.7207	-11.6502	155.9050	-12.3154	-12.2853	-12.2149	148.4240	-11.5539	-11.5228	-11.4784	**162.6810**	**-12.8545**	**-12.8274**	**-12.7570**	146.3740	-11.5499	-11.5228	-11.4524	149.4070	-11.6550	-11.6415	-11.6063
Return Italy CDS spread	-14.3187	-14.2916	-14.2212	**186.5560**	**-14.6845**	**-14.6439**	**-14.5382**	177.8250	-14.0828	-14.0422	-12.9685	184.4520	-14.6426	-14.6020	-14.4986	179.0350	-14.0828	-14.0422	-13.9365	178.2050	-14.0964	-14.0693	13.9989
Return Portugal CDS spread	-11.7290	-11.7020	-11.6315	159.3440	-12.5875	-12.5605	-12.4900	149.2550	-11.7804	-11.7534	-11.6829	**162.0410**	**-12.8033**	**-12.7762**	**-12.7058**	149.3420	-11.7074	-11.6668	-11.5611	148.1400	-11.6912	-11.6641	-11.5937
Return Spain CDS spread	-9.9234	-9.8964	-9.8259	**148.6220**	**-11.7297**	**-11.7027**	**-11.6322**	138.5230	-10.9219	-10.8948	-10.8243	148.1710	-11.6937	-11.6666	-11.5962	139.0100	-10.8808	-10.8402	-10.7345	129.3350	-10.1868	-10.1598	-10.0893
Return Sweden CDS spread	-8.5400	-8.4859	-8.3747	98.3516	-7.7081	-7.6811	-7.6106	106.3200	-8.3456	-8.3185	-8.2481	109.2170	-8.5773	-8.5503	-8.4798	106.7740	-8.3019	-8.2613	-8.1556	**111.4250**	**-8.8376**	**-8.7835**	**-8.6426**
Return UK CDS spread	-13.1186	-13.0916	-13.0211	FLL	FLL	FLL	FLL	175.0370	-13.8430	-13.8159	-13.7455	**175.9660**	**-13.9173**	**-13.8903**	**-13.8198**	175.9610	-13.8369	-13.7963	-13.6906	171.5030	-13.6114	-13.5708	-13.4651

Table 15. presents the number of countries for each out-of-sample period according to the model it forecasted the sovereign CDS volatility the best, respecting the CEE/WE partition. The results confirm my second hypothesis, that CDSs' volatility of the countries from Central and Easter Europe is better forecasted by a different model (GARCH (1,1)) than CDSs' volatility of the countries from Western Europe (mainly GJR-GARCH).

Table 15. Overview of the GARCH models performance by number of CEE vs. WE countries

	CEE countries						WE countries					
Out-of-sample periods	GARCH (1,1	EGAR	GJR-GARCI	APAR	TGARCH	IGARCH	GARCH (1,1	EGARCH	GJR-GARCI	APARCH	TGARCH	IGARCH
Out-of-sample 30 days	4	1	2	2	0	2	0	0	5	2	0	4
Out-of-sample 90 days	5	1	1	0	2	3	1	2	3	2	0	3
Out-of-sample 180 days	8	0	1	1	0	2	0	3	1	5	0	2

Conclusion

Credit default swaps are the most used type of credit derivatives, developed in order to reduce and transfer credit risk. The CDSs can be single-name or multiple-name and they can be also divided between corporate and sovereign.

Volatility is a statistical quantifiable measure of dispersion of the returns, usually directly related with the risk. Forecasting the volatility is very important on risk adjusting measures. GARCH-class models are often used by companies, investors, brokers in analyzing financial data and estimating the volatility of the returns of stocks, bonds, commodities, CDS spreads. Over the years, numerous GARCH-class models have developed in order to capture different characteristics that may influence the volatility (long-rung dynamic dependencies in the conditional variance, more flexibility of the conditional variance, etc.).

I have decided to conduct a research on forecasting performance of six most used GARCH-class models (GARCH (1,1), EGARCH, APARCH, GJR-GARCH, IGARCH, TGARCH) regarding the volatility of sovereign CDS spreads. The decisions is based on a gap in the specialized literature as the majority of the articles focus on how the CDS spreads are determined and influenced, rather than on predicting them.

The sovereign CDSs selected are from the European Union countries, with some exceptions that were excluded due to liquidity problems (Finland, Malta, Netherlands, Greece, and Luxembourg). The period if from 28th of April 2009 and 31st of December 2019 and the approach was to divide the data in two samples: in-sample period from 28th of April 2009 to 31st of December 2018 and out-of-sample periods of 30 days, 90 days and 180 days from the year 2019.

The first objective was to analyze if there exists a single most appropriate GARCH-class models in forecasting the sovereign CDSs volatility or if there are multiple models that fit the predictions. The second objective was to compare the Central and Eastern European countries with the Western European countries and to assess if there are differences between the selected models.

The criteria used for evaluating the forecasting results consist of four statistical values: Log Likelihood, Akaike Info criterion, Schwarz criterion, and Hannan-Quinn criterion.

The results showed that for the 30 days out-of-sample period, GJR-GARCH model was the most appropriate for 7 countries, for the 90 days out-of-sample period both GARCH (1,1) and IGARCH fitted the best 6 countries and for the 180 days out-of-sample period, GARCH (1,1) forecasted the best the volatility of 8 countries' CDS. Regarding the CEE/WE countries analysis, the CDS spreads from CEE are better forecasted by GARCH (1,1) model in all the out-of-sample periods and the CDS spreads from WE are better forecasted by GJR-GARCH (30 days out-of-sample and 90 days out-of-sample), IGARCH (90 days out-of-sample) and APARCH (180 days out-of-sample).

In conclusion, not all the volatilities of the CDS spreads from the European countries are forecasted the best by a single GARCH-class model, but there are different appropriate models for specific sovereign CDSs. In addition, the Central and Eastern European countries are different in terms of volatility compared to the Western European countries which is shown also by the results in terms of most appropriate GARCH-class models.

Limitations & further research

One first limitation comes from the selection of the tested GARCH-class models; there are numerous models and I have used in my analysis only six of them which imply a further need in testing others that may forecast better the sovereign European CDS spreads. Also, the CDS I have analyzed are denominated in euros but there are also sovereign European CDS denominated in US dollars. In addition, the out-of-sample periods may be extended in order to assess the forecasting performance on medium and long-term also.

References

- Agnolucci, P., (2009). Volatility in crude oil futures: A comparison of the predictive ability of GARCH and implied volatility models. *Energy Economics.* 31(2). 316-321. https://doi.org/10.1016/j.eneco.2008.11.001
- Apergis, N., Ajmi, A., (2016). Systematic sovereign risks and asset prices: Evidence from the CDS market, stressed European economies and non-linear causality tests. *Czech Journal of Economics and Finance*. http://repository.psau.edu.sa:80/jspui/handle/123456789/1047
- Avino, D., Nneji, O., (2014). Are CDS spreads predictable? An analysis of linear and non-linear forecasting models. *International Review of Financial Analysis.* 34, 262-274. https://doi.org/10.1016/j.irfa.2014.04.001
- Baillie, R. T., Bollerslev, T., Mikkelsen, H.O., (1996). Fractionally integrated generalized autoregressive conditional heteroskedasticity. *Journal of Econometrics*. 74(1). 3-30. https://doi.org/10.1016/S0304-4076(95)01749-6
- Bannier, C. E., Heidorn, T., Vogel, H.-D. (2014). Characteristics and development of corporate and sovereign CDS. *The Journal of Risk Finance*, 15(5), 482–509. doi:10.1108/jrf-06-2014-0077
- Benbouzid, N., Mallick, S., (2012). Determinants of bank credit default swap spreads: The role of the housing sector. *North America Journal of Economics and Finance*. 24. 243-259. http/dx.doi.org/10.1016/j.najef.2012.10.004
- Benbouzid, N., Mallick, S., Sousa, M (2017). An international forensic perspective of the determinants of bank CDS spreads. *Journal of Financial Stability.* 33. 60-70. https://doi.org/10.1016/j.jfs.2017.10.004 1572-3089/
- Bentes, S. R., (2015). Forecasting volatility in gold returns under the GARCH, IGARCH and FIGARCH frameworks: New evidence. *Physica A: Statistical Mechanics and its Applications*. 438. 355-364. https://doi.org/10.1016/j.physa.2015.07.011
- BIS (2019). Statistical release: OTC derivatives statistics at the end of June 2019. https://www.bis.org/publ/otc_hy1911.pdf

- Bollerslev, T., Mikkelsen, H.O., (1996). Modeling and pricing long memory in stock market volatility. *Journal of Econometrics*. 73(1). 151-185. https://doi.org/10.1016/0304-4076(95)01736-4
- Bollerslev, T. (1986). Generalized autoregressive conditional heteroskedasticity. *Journal of Econometrics* 31(3), 307-32. https://doi.org/10.1016/0304-4076(86)90063-1
- Bouri, E., Boyrie, M., Pavlovac, I., (2017). Volatility transmission from commodity markets to sovereign CDS spreads in emerging and frontier countries*. International Review of Financial Analysis*. 49. 155-165. https://doi.org/10.1016/j.irfa.2016.11.001
- Byström, H. (2016). Credit-implied forward volatility and volatility expectations. *Finance Research Letters.* 16. 132-138. https://doi.org/10.1016/j.frl.2015.10.027
- Cao, C., Yu, F., Zhongd, Z., (2010). The information content of option-implied volatility for credit default swap valuation. *Journal of Financial Markets*. 13(3). 321-343. https://doi.org/10.1016/j.finmar.2010.01.002
- Cheong Vee, DN, Gonpot, PN., Sookia, N. (2011) Forecasting Volatility of USD/MUR Exchange Rate using a GARCH (1,1) model with GED and Student's-t errors. DOI: 10.4314/umrj.v17i1.70728
- Corzo Santamaría, M.T.; Gómez Biscarri, J.; Lazcano Benito, L. (2014). Financial crises and the transfer of risks between the private and public sectors: Evidence from European financial markets. Span. Rev. Financ. Econ. 12. 1–14. http://hdl.handle.net/11531/16909
- Davidson, J. (2004). Moment and Memory Properties of Linear Conditional Heteroscedasticity Models, and a New Model, *Journal of Business & Economic Statistics*, 22:1, 16-29, DOI: 10.1198/073500103288619359
- Ding, Z., Granger. W. J., Engle, R. (1993), A Long Memory Property of Stock Market Returns and a New Model. *Journal of Empirical Finance*. 83-106. doi/abs/10.5555/781840.781860
- Engle, R. (1982). Autoregressive Conditional Heteroscedasticity with Estimates of the Variance of United Kingdom Inflation. *Econometrica*, 50(4), 987-1007. doi:10.2307/1912773

- Engle, R., Bollerslev T. (1986) Modelling the persistence of conditional variances. *Econometric reviews*. 5(1). 1–50.
- Fontana, A., Scheicher, M., (2016). An analysis of euro area sovereign CDS and their relation with government bonds. *Journal of Banking & Finance*. 62. 126-140. https://doi.org/10.1016/j.jbankfin.2015.10.010
- Forgo, B, Jevcak, A. (2015). Economic convergence of Central and Eastern European EU member states over the last decade (2004-2014), European Commission. https://ec.europa.eu/info/sites/info/files/economy-finance/dp001_en.pdf
- Girish, V.S. (2010), A brief history of derivatives. The banking and financial world.
- Glosten, L. R., Jagannathan, R., Runkle, D. E., (1993). On the Relation between the Expected Value and the Volatility of the Nominal Excess Return on Stocks. *Journal of Empirical Finance* 48(5). https://doi.org/10.1111/j.1540-6261.1993.tb05128.x
- Gokbulut, R. I., Pekkaya, M. (2014). Estimating and Forecasting Volatility of Financial Markets Using Asymmetric GARCH Models: An Application on Turkish Financial Markets. DOI:10.5539/ijef.v6n4p23
- Hafner, C. M., Herwartz, H., (2008). Testing for Causality in Variance Using Multivariate GARCH Models. *Annales d'Économie et de Statistique*. 89. 215-241. DOI: 10.2307/27715168
- Hasan, I., Liu, L., Zhang, G. (2016) The Determinants of Global Bank Credit-Default-Swap Spreads. *Journal of Financial Services Research*. 50. 275-309. 10.1007/s10693-015-0232-z
- ISDA (2012), Credit Derivatives Physical Settlement Matrix
- ISDA (2019). Global Credit Default Swaps Market Study. https://www.isda.org/a/JUPTE/Global-CDS-Market-Study.pdf
- ISDA (2020), Swaps Info Full Year 2019 and Fourth Quarter of 2019 Review
- Kang, S. H., Kang, S-M., Yoon, S-M., (2009). Forecasting volatility of crude oil markets. *Energy Economics.* 31(1). 119-125. https://doi.org/10.1016/j.eneco.2008.09.006
- Krishnan, C.N.V., Ritchken, P. H., Thomson, J. B., (2010). Predicting credit spreads. 19(4). 529-563. https://doi.org/10.1016/j.jfi.2009.02.004

- Kocsis, Z, Monostori, Z, (2016). The role of country-specific fundamentals in sovereign CDS spreads: Eastern European experiences. *Emerging Markets Review* 27, issue C, 140-168. 10.1016/j.ememar.2016.05.003
- Liu, H-C., Hung, J-C, (2010). Forecasting S&P-100 stock index volatility: The role of volatility asymmetry and distributional assumption in GARCH models. *Expert Systems with Applications*. 37(7). 4928-4934. https://doi.org/10.1016/j.eswa.2009.12.022
- Mohammadi, H., Su, L., (2010). International evidence on crude oil price dynamics: Applications of ARIMA-GARCH models. *Energy Economics*. 32(5). 1001-1008. https://doi.org/10.1016/j.eneco.2010.04.009
- Musunuru, N., Yu M., Larson, A. (2013). Forecasting volatility of returns for corn using GARCH models. *Texas Journal of Agriculture and Natural Resources*. 26. 42-56.
- Nelson, D. (1991). Conditional Heteroskedasticity in Asset Returns: A New Approach. *Econometrica*, 59(2), 347-370. doi:10.2307/2938260
- Cheong Vee, N, Gonpot, P., Sookia, N., (2011). Forecasting Volatility of USD/MUR Exchange Rate using a GARCH (1,1) model with GED and Student's-t errors. *University of Mauritius Research Journal*. 17. 10.4314/umrj.v17i1.70728.
- Onwukwe, C., Bassey, B.E.E., Idongesit, I. (2011). On Modeling the Volatility of Nigerian Stock Returns Using GARCH Models. *Journal of Mathematics Research*. 3. 10.5539/jmr.v3n4p31.
- Pilbeam, K., Langeland, K. N., (2015). Forecasting exchange rate volatility: GARCH models versus implied volatility forecasts. *International Economics and Economic Policy*
- Sabkha, S, de Peretti, C, Hmaied, D, (2018) Forecasting sovereign CDS volatility: A comparison of univariate GARCH-class models. *hal-01769390*
- Samaniego-Medina, R., Trujillo-Ponce, A., Parrado-Mart´inez, P., and di Pietro, F., (2016). Determinants of bank CDS spreads in Europe, *Journal of Economics and Business*, http://dx.doi.org/10.1016/j.jeconbus.2016.03.001

- Sharma, S. S., Thuraisamy, K., (2013). Oil price uncertainty and sovereign risk: Evidence from Asian economies. *Journal of Asian Economics*. 28. 51-57. https://doi.org/10.1016/j.asieco.2013.06.001
- Shen, Z., Ritter, M., (2016). Forecasting volatility of wind power production. *Applied Energy.* 176. 295-308. https://doi.org/10.1016/j.apenergy.2016.05.071
- Srinivasan, P., Ibrahim, P., (2010). Forecasting Stock Market Volatility of Bse-30 Index Using Garch Models. *Asia-Pacific Journal of Management Research and Innovation*. https://doi.org/10.1177/097324701000600304
- Srivastava, S., Lin, H., Premachandra, I. M., Roberts H., (2016). Global risk spillover and the predictability of sovereign CDS spread: International evidence. *International Review of Economics & Finance*. 41. 371-390. https://doi.org/10.1016/j.iref.2015.10.047
- Tse, Y. K. (1998). The conditional heteroscedasticity of the yen–dollar exchange rate. *Journal of Applied Econometrics.* 13(1). https://doi.org/10.1002/(SICI)1099-1255(199801/02)13:1<49::AID-JAE459>3.0.CO;2-O
- Wang, Y., Wu, C., (2012). Forecasting energy market volatility using GARCH models: Can multivariate models beat univariate models?. *Energy Economics.* 34(6). 2167-2181. https://doi.org/10.1016/j.eneco.2012.03.010
- Wei, Y., Wang, Y., Huang, D., (2010). Forecasting crude oil market volatility: Further evidence using GARCH-class models. *Energy Economics.* 32(6). 1477-1484. https://doi.org/10.1016/j.eneco.2010.07.009
- Zakoian, J-M., (1994). Threshold heteroskedastic models. *Journal of Economic Dynamics and Control.* 18(5). 931-955. https://doi.org/10.1016/0165-1889(94)90039-6

The Central Banks. An Analysis of Inflation and Independence

Sebastian Mariș

Student at University of Essex (M.A Global and Comparative Politics)

This paper contains 14 pages, excluding first page and bibliography

Abstract

In the following paper we aim to test if the Central Bank Independence (CBI) truly affects inflation. In recent years, studies have shown that there is no significant relationship between the strength of Central Bank Independence and the Consumer Price Index (CPI) growth rate in developed countries and developing countries. This challenged the notion that controlling inflation has been a justification for the CBI. We aim to compare 15 developed and 10 developing countries. If CBI is truly that important we should expect comparable or similar results in both groups.

Introduction

The field of research on Central Banks became important especially after 1990, when a wave of countries in the world began to grant independence to the central banks. In developed countries, it is common to delegate the implementation of monetary policies to a central bank, some distance from the government. In democracies, theories that justify delegating monetary policy to non-elected professionals have been discussed in both economic and political terms.

One of the key reasons for Central Bank Independence (CBI) is that its decoupling from political pressure positively contributes to price stability. However, some previous studies argue that CBI does not affect price stability in developed countries. For example, R.Kokoszczyński and J.Mackiewicz-Łyziak (2020) state that the CBI is important in an underdeveloped economy but not in a developed one. If the CBI does not contribute to price stability, the legitimacy of entrusting monetary policy decisions to unelected technocracy will be upset.

If the CBI does not contribute to price stability, how is it justified to delegate monetary policy decisions to an independent central bank? Since the global financial crisis, monetary policy of central banks has not only increased or decreased interest rates as in the past, but also implemented more discretionary policies. They have purchased securities with unprecedented amounts of money and have become implicitly involved in fiscal policy decisions (Fernández-Albertos, J. (2015). The US Federal Reserve's balance sheet more than doubled in the six months following the crisis, growing significantly faster than the average annual rate of 6.25% over the past nine years. Although the ECB responded slower, its balance sheet increased at a rate of 70.88% annually between May 2011 and March 2012 (Cukierman A. 2013). At the same time, they face the challenge of ending monetary easing. Given the negative effects of financial tightening, the decision is more political. Today's central bankers are required to make such difficult and political decisions. However, it would be naive to think that central bankers are merely neutral technocrats who don't have their own preferences. Chris Adolph (2013) created and analyzed its own dataset containing the career and educational background of about 600 central bankers from 1950 to 2000. The results showed that the careers of the central bankers influenced their policy decisions. In other words, it has been shown that governments can exert democratic control over monetary policy through the central banker appointment process.

Given that central banks are under the democratic control of the government in the long run and the CBI only ensures the independence of short-term policy decisions, what are the reasons for such central bank independence? Shouldn't elected national representatives be responsible for policy decisions? It is important to remember that central bank independence is about avoiding short-term motivated policy decisions.

Therefore, it is necessary to re-examine the relationship between the CBI and CPI. In the first place, price indices are not always single, and tend to differ greatly depending on how the indicators are taken.

In this article, I will re-examine whether the CBI is contributing to price stability by using multiple price indices with different time and target items.

Literature Review

Much has been written on the subject of Central Banks and their independence, and the school of thought that support the idea that the Central Banks should be independent in relation to politics is the dominant one. Central Bank Independence (CBI) means that monetary policy is delegated to unelected officials and the government's influence on monetary policy is therefore restricted. Alesina and Tabellini (2008) argue that the delegation of decision-making authority is beneficial in at least three cases: the tasks are technical in nature, they are difficult to monitor, and when policymakers do not have distributional effects. The traditional idea of CBI rests on countering inflationary tendencies that could occur in the absence of an independent central bank. One reason is the political pressure which aims to use the central bank's power to issue money as a way to finance their redistributive electoral program. Politicians can also abuse their position to influence the central bank to accept an economic program which is damaging the economy, but it can bring votes on short term. Bernanke (2010) argues that lack of central bank's independence can lead to higher inflation on longer run, and a conservative central bank is more prone to keep inflation low. Furthermore Klomp and de Haan (2010) conclude that countries with independent Central Bank record on average lower inflation compared with countries with a state-controlled Bank.

Some authors claim that although the Central Bank should be independent, it should not be actually independent in setting its own goals, such as monetary policy (Mishkin, 2011). The argument is used especially in democracies, where the government is accountable to the electorate. Therefore the monetary policy should be established by political authorities and conducted by the Central Bank. There are some authors such as Peter Hall (1993) claiming low inflation is not actually caused by the degree of independence of Central Bank, but rather caused by institutional and systemic structure. In his study he concluded that the economic coordination and the system of wage bargaining in Germany actually play a consistent role at the level of unemployment, helping the Central Bank more than its independence does. A recent study made by R. Kokoszczyński and J. Mackiewicz-Łyziak (2020) used the annual percentage change of the CPI index as the dependent variable. The explanatory variables used were GDP per capita growth rate (annual,%), general government budget balance (% of GDP), and the sum of imports and exports in relation to GDP as openness of the economy. Regarding the explanatory variables, they concluded that trade openness had no significant effect on inflation in developed countries. On the other hand, GDP growth and budget surpluses will reduce inflation. However, the paper of R. Kokoszczyński and J. Mackiewicz-Łyziak (2020) has a notable limitation, it is a cross-sectional study not a longitudinal study and this might affect its scientific conclusion. Due the fact that their study is concentrated only on a short period after the financial crisis, we believe a period of 20 years could offer more persuasive scientific results. Therefore the aim of our paper is to study how the CBI affected both developed and non-developed countries between 2000 and 2019.

Theory and Research Design

Due the fact that few studies are made on Eastern Europe, we decided to take most of our cases from this part of the world. A small, but concentrated number of countries in a region, could easily offer some results very specific to that region.

Helmut Wagner(1999) argues in his paper that in developing countries the CBI is actually more on paper than in reality. His historical analysis argues that the entire Central Bank system had to be created from ashes in the post-communist countries, which caused harsh legislative problems. Secondly, he argues that this new system, which is adapted to the market economy requires a very long time to become functionable. Last but not least, the countries in Eastern Europe adopted a Western-type central bank, and within 6 years (1991-1996) the former socialist countries changed the functions and the laws of this system at least three times a year.

What this paper wants to clarify is whether the CBI will affect price stability in developed and developing countries. And is there any change in the impact of the CBI before and after the global financial crisis? As we have noticed the literature is divided into Schools of Thought that either support or not the independence of the central bank. **The independent variable** is Central Bank Independence (Index) and the **dependent variable** is Consumer Price Index (For All Items and Food and Non-Alcoholic Beverages) along with GDP/Cap Growth as **control variable**.

As the existing studies show, even if there is a correlation between high CBI and low inflation, it cannot immediately lead to a causal relationship (Mas 1995). Some theories argue that this is the result of the political influence of financial institutions (Posen 1995). Nevertheless, it is necessary to re-examine whether there is really no correlation between CPI and CBI in developed and developing countries in discussing the legitimacy of the CBI.

The hypothesis in this study was that the correlation between CBI and CPI in developed and developing countries could not be confirmed due to the temporary factor of the financial crisis, and by observing long-term data after and before the financial crisis, we can establish a correlation. We used available data in OECD and World Bank.

Data

This paper examines the relationship between CBI and inflation over the period 2001-2019. However, in order to observe changes in the period before and after the global financial crisis, this paper divides the same period into two periods, 2000 to 2009 and 2010 to 2019, and makes a comparison. Our paper analyzes 15 developed countries (Greece, United Kingdom, Sweden, France, Australia, Switzerland, New Zealand, United States, Luxembourg, Japan, Germany, Denmark, Italy, Canada and Portugal) and 10 non-developed countries (Brazil, Poland, Slovak Republic, Mexico, Czech Republic, Russia, Lithuania, Slovenia, Hungary and Estonia). In this paper, we use the CBIW index provided by Dincer, N.N. and Eichengreen, B (2014) as the CBI index. This is the CWN index recalculated by Dincer, N.N. and Eichengreen, B during the period 1998-2010. The index reflects the independence of the chief executive officer (CEO) of the central bank, its independence in policy formulation, its objective or mandate, and the stringency of limits on its lending to the public sector.

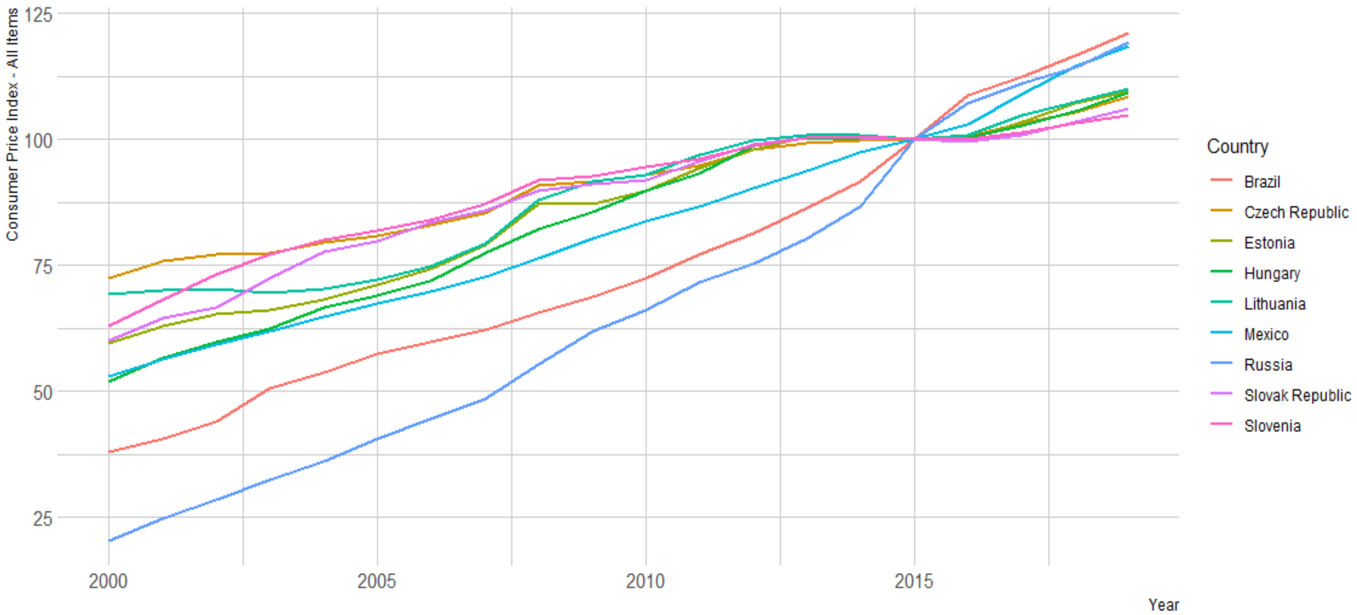
The dependent variable is the consumer price index. This paper uses the consumer price index of all items and the index of food and non-alcoholic beverages among the consumer price indexes provided by OECD stat. For the CPI, this paper uses the annual rate of change for the periods 2001-2010 and 2010-2019, respectively.

The reason for using the CPI for food and non-alcoholic beverages is to eliminate the impact of digital products as much as possible. To accurately measure the CPI, it is necessary to compare prices of goods of the same quality. However, since ICT products have various functions, it is difficult to determine which products have the same quality. A method called Hedonic Quality Adjustment is used for price adjustment of ICT products, but it is controversial whether this method can accurately judge products of the same quality. The reference year was changed to 2015 by OECD. In these cases of shorter time series, the OECD Secretariat, ensures there is no loss of time series for users, estimates the missing data for the main expenditure components of GDP in order to publish historical data from 1960 (where possible). The estimation is undertaken using the current systems of accounts and linking to older systems based on different methodology in order to obtain the longer time series. The method used by the Secretariat to link two time series from two different methodologies is as follows: for each individual series, the ratio between the new methodology data and the old methodology data in the first common year is calculated. This ratio is then multiplied by old methodology series for the time period that data have not been provided. The same method is applied to both current and volume estimates data. Also historical growth rates are derived from estimated volume data.

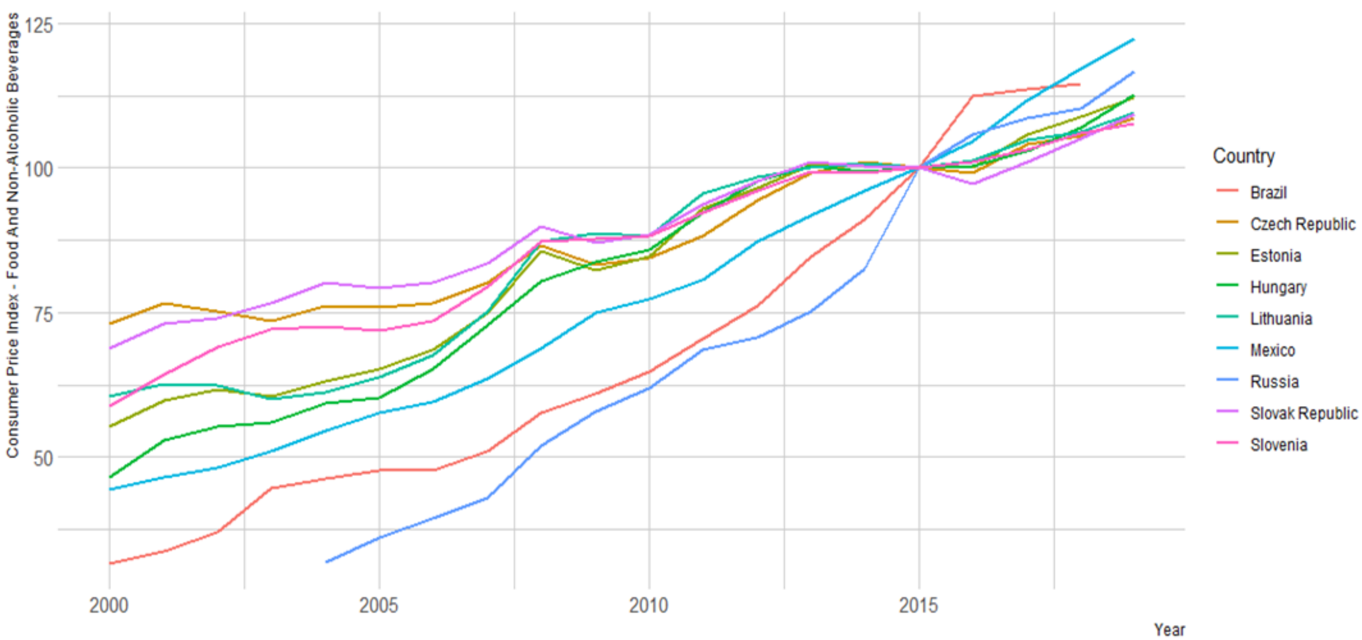
Analysis and Results

Changes in CPI suggest that CPI (food and non-alcoholic beverages) fluctuated more overall than CPI (all items) in developed countries, and that prices have dropped significantly due to the effects of the global financial crisis

The results of the regression analysis indicate that in developed countries, although the CBI appear to have a significant effect on CPI (all items) and Food and Non-Alcoholic Beverages between 2001 and 2010, the relation seem to be positive, while the effect of GDP is negative. Between 2010 and 2019, the CBI appears to lack any kind of effect on CPI. The lack of a significant correlation between CBI and CPI between 2010 and 2019 may be due to one reason: prices have fluctuated significantly, irrespective of CBI, due to the effects of the global financial crisis. The other reason may be that the central banking system was revised in the aftermath of the global financial crisis to be more in line with monetary policy decisions. According to R. Kokoszczyński and J. Mackiewicz-Łyziak (2020), in developed countries, the CBI continued to increase until around 2007 or 2008, but institutional changes were made to reduce it thereafter.

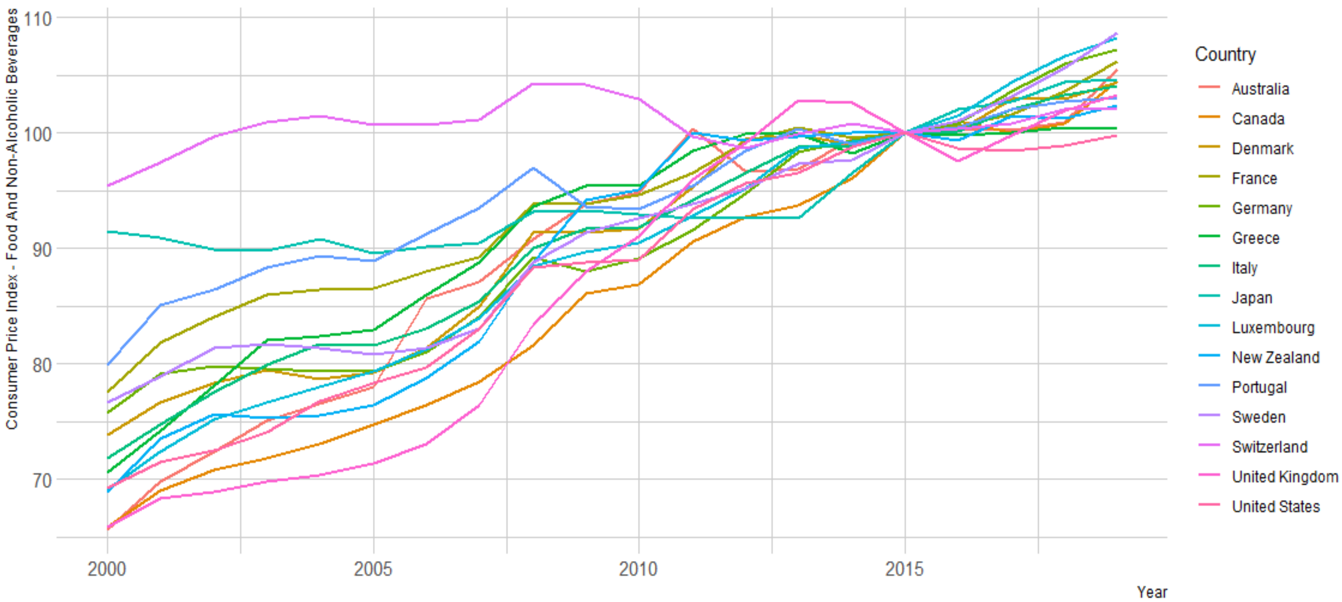


1

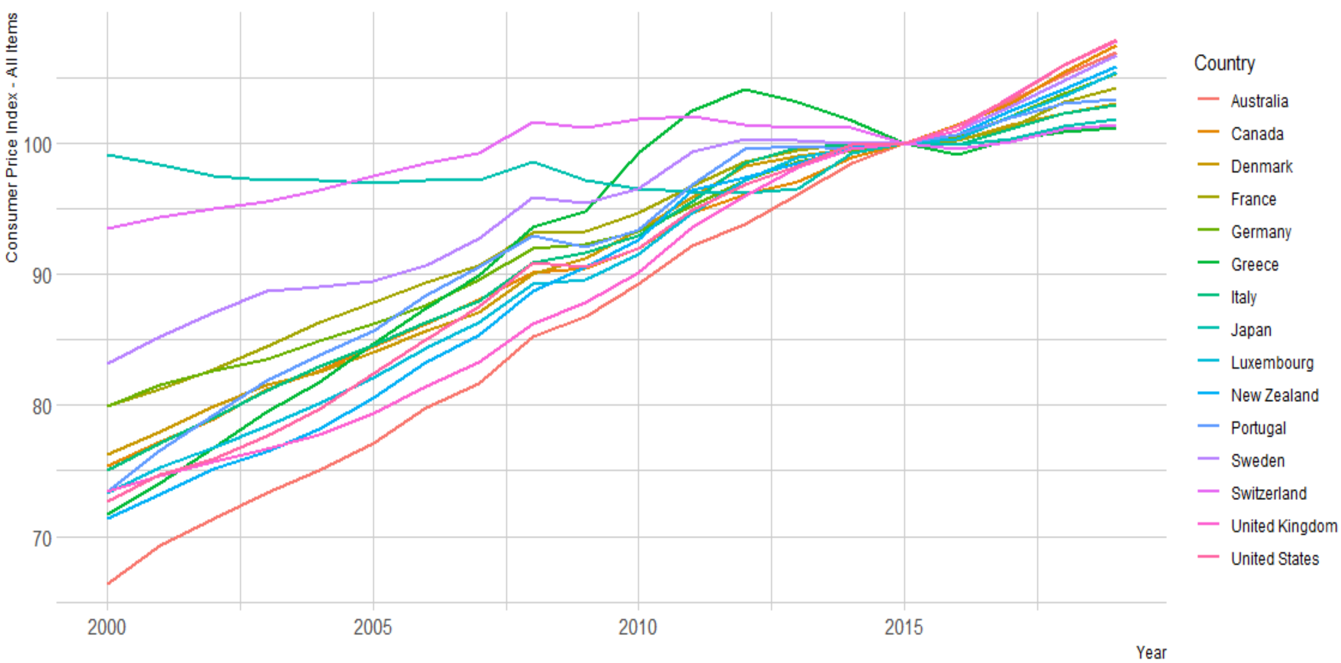


2

[1] Source: OECD, Developing Countries
[2] Source: OECD, Developing Countries



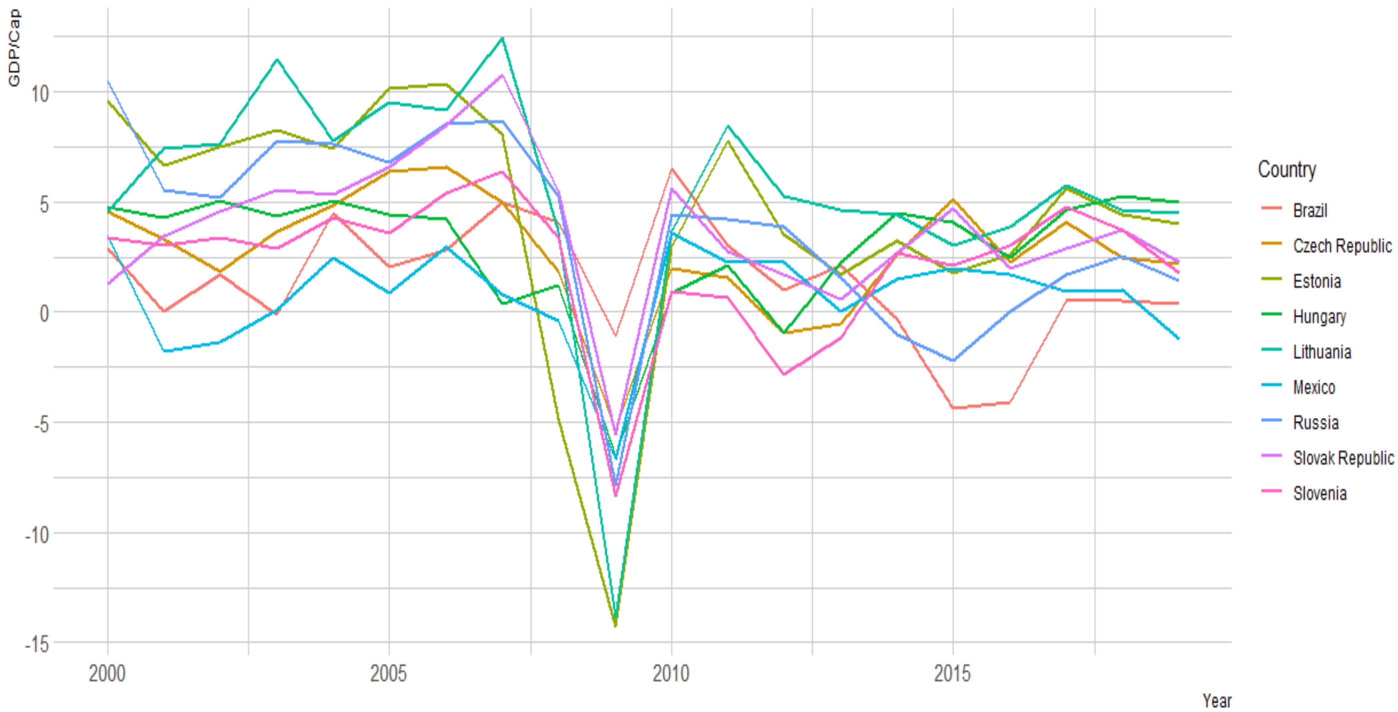
3



4

[3] Source: OECD, Developed Countries

[4] Source: OECD, Developed Countries

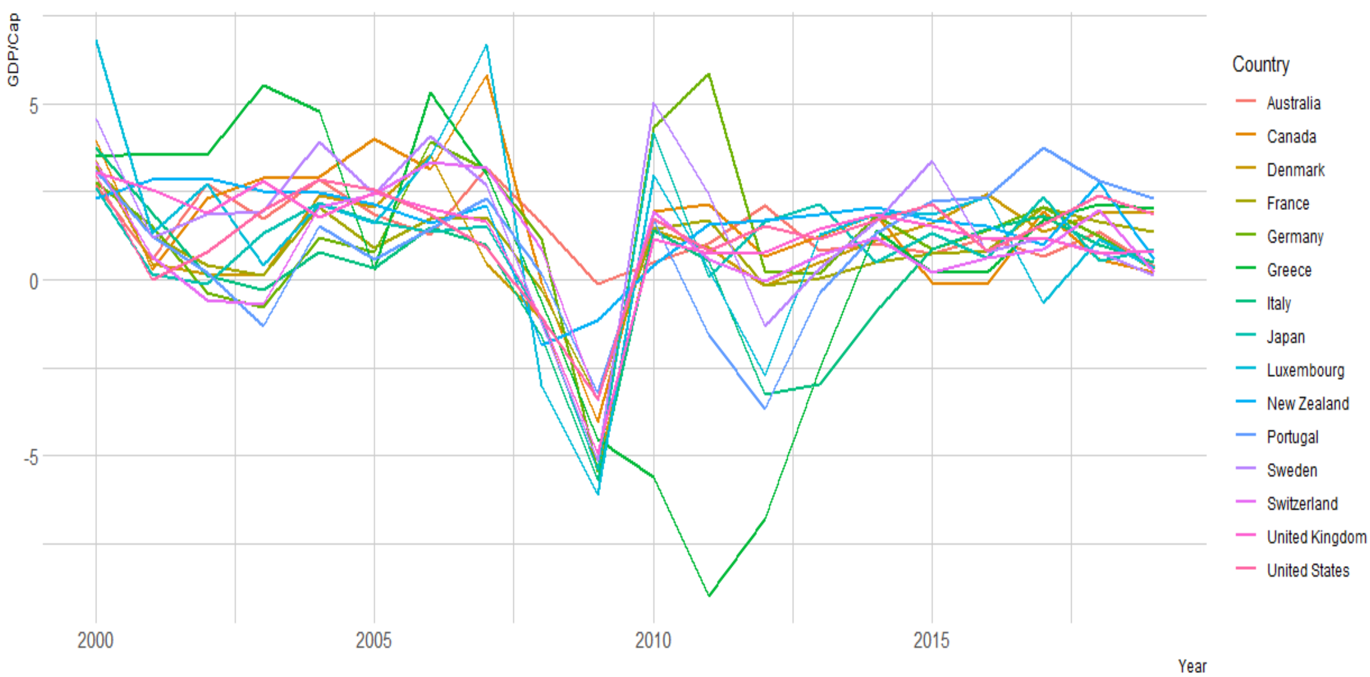


[5]

Regarding the developing countries, we noticed that CBI is significantly associated with CPI (All Items) between 2000 and 2019, which could mean during this time the Central Bank's policy was made especially for this category. However, analyzing both periods separately we observe that there is no significant relationship between CBI and CPI. An explanation for this result could be that all our cases here are former dictatorships. The transition especially from Communism to free market came along with heavy social and economic problems (such as high inflation and significant price fluctuations) and most importantly, with weak institutions, which might explain that the CBI is useless in a context like this. Furthermore, the demand for redistribution in these countries could be higher compared to the developed countries, which directly requires a pressure from the political parties on the Central Bank. For the period 2010-

[5] Source: World Bank Data, Developing Countries

2019, we can notice from the Graph, that developing countries were hit worse than developed countries by the financial crisis in terms of GDP. Based on these results, the financial crisis could have created so many economic problems in both developed and developing countries that they actually made CBI irrelevant.



6

---

[6] Source: World Bank Data, Developed Countries

	Dependent variable:					
	All.2000.2019 (1)	All.2000.2009 (2)	All.2010.2019 (3)	Food.2000.2019 (4)	Food.2000.2009 (5)	Food.2010.2019 (6)
GDP Growth (2000-2019)	-0.909***			-1.242***		
	(0.286)			(0.316)		
CBI(2000-2019)	0.784***			1.124***		
	(0.224)			(0.248)		
GDP(2000-2009)		-1.181***			-1.613***	
		(0.226)			(0.233)	
CBI(2000-2009)		1.521***			2.306***	
		(0.235)			(0.231)	
GDP(2010-2019)			-0.239			-0.211
			(0.243)			(0.240)
CBI(2010-2019)			0.134			0.174
			(0.121)			(0.136)
Constant	92.501***	84.688***	99.796***	91.012***	82.016***	99.147***
	(0.695)	(0.655)	(0.453)	(0.769)	(0.654)	(0.478)
Observations	280	140	140	280	140	140
R2	0.077	0.340	0.017	0.119	0.511	0.020
Adjusted R2	0.071	0.331	0.003	0.113	0.504	0.005
Residual Std. Error	9.118 (df = 277)	6.340 (df = 137)	3.685 (df = 137)	10.081 (df = 277)	6.256 (df = 137)	4.110 (df = 137)
F Statistic	11.625*** (df = 2; 277)	35.344*** (df = 2; 137)	1.184 (df = 2; 137)	18.690*** (df = 2; 277)	71.563*** (df = 2; 137)	1.372 (df = 2; 137)
Note:						*p<0.1; **p<0.05; ***p<0.01

7

	Dependent variable:					
	All.2000.2019 (1)	All.2000.2009 (2)	All It.2010.2019 (3)	Food.2000.2019 (4)	Food.2000.2009 (5)	Food.2010.2019 (6)
GDP Growth(2000.2019)	-1.487***			-1.253***		
	(0.366)			(0.380)		
CBI (2000-2019)	24.970*			16.761		
	(14.123)			(14.501)		
GDP(2000-2009)		-1.043***			-0.898***	
		(0.320)			(0.284)	
CBI(2000-2009)		10.675			-5.313	
		(16.274)			(13.901)	
GDP(2010-2019)			-0.528			0.442
			(0.526)			(0.548)
CBI(2010-2019)			11.509			8.960
			(10.376)			(12.310)
Constant	73.067***	66.985***	93.074***	76.330***	74.401***	91.316***
	(9.296)	(10.686)	(6.506)	(9.520)	(9.164)	(7.755)
Observations	160	80	80	156	76	80
R2	0.104	0.125	0.020	0.069	0.122	0.025
Adjusted R2	0.093	0.102	-0.005	0.057	0.098	-0.001
Residual Std. Error	18.590 (df = 157)	15.032 (df = 77)	8.957 (df = 77)	19.033 (df = 153)	12.801 (df = 73)	10.712 (df = 77)
F Statistic	9.155*** (df = 2; 157)	5.499*** (df = 2; 77)	0.800 (df = 2; 77)	5.710*** (df = 2; 153)	5.089*** (df = 2; 73)	0.972 (df = 2; 77)
Note:						*p<0.1; **p<0.05; ***p<0.01

8

[7] Regression Result for Developed Countries

[8] Regression Result for Developing Countries

Conclusion

This paper is significant in using the latest consumer price index data to examine the relationship between CBI and CPI after and before the global financial crisis using long-term data.

In developed countries the results confirm that there is a correlation between CBI and CPI both for All Items and Food and Non-Alcoholic Beverages (all items) for the period from 2000 to 2019. Also, when observed over a long period of time from 2001 to 2019, it was statistically significantly confirmed but there was a positive correlation between the two. Looking specifically to 2010-2019 period, we observe there is no strong association between CBI and CPI.

From 2001 to 2010, a positive correlation was found between CBI and CPI (for both all items and food and non-alcoholic beverages). On the other hand, no correlation was confirmed between 2010 and 2018, suggesting that monetary policy may have changed. It has been confirmed that there is a negative correlation between GDP growth rate and CPI increase rate.

Regarding the developing countries, we noticed that CBI does not play a significant role, not even on long term. The problems the post-communist countries faced and are facing along with their current internal political structure could represent an explanation for the lack of relevance of CBI. As Peter Hall(1993) mentioned in his study, the structure of the system could be actually the one which is keeping inflation under control and not the CBI.

Given the correlation between the CBI and inflation before the financial crisis, it may be justified to maintain central bank independence to avoid unexpected inflation as a response to elections. Today, the policy instruments of central banks are diversifying, and their purchase of securities and government bonds can easily be tied to the interests of certain companies and governments. Central bank independence from politics may help to separate monetary policy from the existence of dissent and implement bold policies from a long-term perspective. Central bank independence from politics may help to separate monetary policy from the existence of dissent and implement bold policies from a long-term perspective.

This paper does not want to make a case against Central Bank Independence because the limits of our essay are obvious. First, a more consistent study which could embody a larger number of cases could offer a more persuasive scientific conclusion. Secondly, further research is needed on how the Central Bank's policies changed after the Financial Crisis. Further research is needed to see if the context of post-authoritarian and post-totalitarian countries truly affects the economy in such a way that the CBI is irrelevant.

Bibliography

Alesina, A., and G. Tabellini. 2008. Bureaucrats or politicians? Part II: multiple policy tasks. Journal of Public Economics 92: 426–447

Barro, R.J. and Gordon, D.B., 1983. Rules, discretion and reputation in a model of monetary policy. *Journal of monetary economics, 12(1)*, pp.101-121.

Bernanke, B.S. 2010. Central bank independence, transparency, and accountability. Speech of Chairmann Ben S. Bernanke at the Institute for Monetary and Economic Studies International Conference, Bank of Japan, Tokyo, Japan May 25, 2010

Cukierman, A., 2013. Monetary policy and institutions before, during, and after the global financial crisis. *Journal of Financial Stability, 9(3)*, pp.373-384.

Dincer, N.N. and Eichengreen, B., 2013. Central bank transparency and independence: updates and new measures.

Fernández-Albertos, J.,2015. The politics of central bank independence. *Annual Review of Political Science, 18*, 217-237.

Garriga, A.C., 2016. Central bank independence in the world: A new data set. *International Interactions, 42(5)*, pp.849-868.

Hall, P., 1993. *Central Bank Independence And Coordinated Wage Bargaining: Their Interaction In Germany*. Center for European Studies, Harvard University.

Klomp, J., and J. de Haan. 2010. Inflation and central bank independence: A meta regression analysis. Journal of Economic Surveys 24 (4): 593–621.

Kydland, F.E. and Prescott, E.C., 1977. Rules rather than discretion: The inconsistency of optimal plans. *Journal of political economy, 85(3)*, pp.473-491.

Mas, I., 1995. Central bank independence: A critical view from a developing country perspective. *World Development, 23(10)*, pp.1639-1652.

Masciandaro, D. and Romelli, D., 2015. Ups and downs of central bank independence from the Great Inflation to the Great Recession: theory, institutions and empirics. *Financial History Review, 22(3)*, pp.259-289.

Posen, A.S., 1995. Declarations are not enough: financial sector sources of central bank independence. *NBER macroeconomics annual, 10*, pp.253-274.

R. Kokoszczyński, J. Mackiewicz-Łyziak, 2020. Central bank independence and inflation—Old story told anew. *Int J Fin Econ*. 2020; 25: 72– 89

Rogoff, K., 1985. The optimal degree of commitment to an intermediate monetary target. *The quarterly journal of economics, 100(4)*, pp.1169-1189.

Wagner.H, 1999. Central Bank Independence and the Lessons for Transitiona Economies from Developed and Developing Countries. Comparative Economic Studies, XLI, no.4(Winter 1999), 1-22.