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The Greek debt crisis through the lens of time series and multiscale analysis

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Abstract: The paper examines how co-movements between bond markets of Greece and four other European economies (Belgium, Germany, Portugal, and the UK) change after the beginning of the Greek debt crisis in 2009. We study 10-year-bond yields through time series and multiscale analysis, so as to conclude on presence of contagion, divergence and structural breaks. Major results suggest that there is contagion to Portugal. Yet, no evidence of contagion is identified with regard to the rest of the studied markets. Moreover, there are signs of divergence between Greece and Germany, as well as between Greece and Belgium – economies that seem to have moved together before the crisis. Our study demonstrates that application of multiscale analysis reveals information that is otherwise not that obvious, thus explaining processes that took place just after the crisis.

Keywords: Greek debt crisis, ARMAX, wavelet transform, multiscale analysis

JEL: G010 Financial Crises, C100 Econometric and Statistical Methods and Methodology: General

I. INTRODUCTION

Up to date numerous research papers are engaged with the analysis, implications and possible solutions of the Greek debt crisis, such as (Pascual & Ghezzi, 2011), (Hallerberg, 2010) and (Kouretas, 2010). Yet, another important research strand aims to estimate its spillover effects mainly in terms of detecting “contagion” as defined in (Forbes & Rigobon, 2002). Among others, (Cronin, et al., 2016) test for contagion between Eurozone bond markets during the sovereign debt crisis. Using a three regime Markov-switching VAR, they identify two distinct crisis phases (“bad” and “ugly”). There is a trace of contagion, stronger through the intensive phase of the crisis. The phenomenon is not associated with the PIGS countries only, contagion is also spread from the core group (Finland, the Netherlands, Austria, Belgium). Furthermore, (Beirne & Fratzscher, 2013) recognise 3 different types of contagion – fundamentals (“wake-up call”), regional spillover and herding. While the fundamentals contagion was strongly present, the regional spillovers were found to decrease. The herding contagion piqued around certain temporal and geographical points.

(Bhanot, et al., 2014) investigate the effect of changes in Greek sovereign yield spreads on abnormal returns of financial sector stocks in the PIGS countries during the Greek debt crisis. Using a multivariate GARCH model, they conclude that news on the Greek issue enhance significantly the spillover from the Greek bond market, as additional information to investors is given, hinting at the possible future of the Eurozone financial sector. Furthermore, they find evidence of direct spillover from the Greek bond market to other country stock markets through increases in the spreads of the domestic bond market. The method was drawn from (Mink, et al., 2013). A similar approach is used in (Kenourgios, 2014) – a GJR-GARCH model, leading to the findings that there is significant contagion for the analyzed countries (USA, France, Germany, UK, Switzerland) in the first stage of the Greek debt crisis. In (Philippasa & Siriopoulos, 2013) a copula is introduced after the GJR-GARCH model, estimating the contagion potential among the EMU countries. (Ahmad, et al., 2013) presents a DCC-GARCH model, confirming the existence of herding contagion from GIPSI to BRIICKS countries.

In (Gómez-Puig & Sosvilla-Rivero, 2014) the authors test for Granger-causality relationships between markets and then determine the breakpoints in the development of relationships thus detecting existence of contagion episodes. Other research methods include CoVaR and copula in (Reboredo & Ugolini, 2015), wavelet and variational decomposition, followed by VaR in (Shahzada, et al., 2016), ARMA-EGARCH and copula in (Silvapulle, et al., 2016), a CIR model ("to eliminate the effects of changes in the ECB policy rate on individual sovereign debt yields"), combined with VaR, in (Suh, 2015). The basic approach of (Dewandaru, et al., 2016) is the utilization of discrete and continuous wavelet transformation in order to detect possible contagion among the Eurozone equity markets.

This paper constitutes a contribution to the aforementioned topics. On one hand, we study pre- and post-crisis relationship, so as to identify any changes and breaks. Apart from contagion, the paper provides divergence analysis, which is a major contribution. On the other hand, we deepen the understanding of these divergence processes through multiscale analysis, which is another important contribution.

The rest of the paper is structured as follows. Section 2 provides an overview of employed methodology. Section 3 describes dataset characteristics and presents major results, followed by a discussion. Section 4 concludes.

II. METHODOLOGY

The methodology combines both classical and novel techniques in order to deliver robustness of results and obtain better understanding of spillover and divergence processes. We split data into two subsamples – before and after the crisis, thus we capture changes in relationships and occurrence of structural breaks.

The first stage of our analysis relies on classical time series modelling. In particular, we estimate a grid of ARIMA and ARMAX models over the pre- and post-crisis subsamples in order to identify significant dependencies during both of the periods. For a stationary sequence $\{y_t, t = 1, \dots, T\}$, the single ARMAX equation is defined as follows[1]:

$$\alpha(L)y_t = \sum_{i=1}^{k} \eta_i(L)x_{it} + \theta(L)\varepsilon_t, \quad (1)$$

where L is the backshift operator, $\{\varepsilon_t\}$ is a white noise process with constant variance σ^2,

$\alpha(L) = 1 - \sum_{j=1}^{p} \alpha_j L^j$,

$\theta(L) = 1 - \sum_{j=1}^{q} \theta_j L^j$,

$\eta_i(L) = \eta_{i0} - \sum_{j=1}^{s_i} \eta_{ij} L^j$.

All roots of $\alpha(L)$ and $\theta(L)$ are assumed to lie outside the unit circle.

We use Akaike and Schwarz information criteria to perform model selection out of all ARMA and ARMAX combinations for both of the subsample periods. We should note that eq.(1) is fit to the first differences[2] of 10-year bond yields of Germany, Portugal, the UK, and Belgium, where the exogenous explanatory variable is the first differenced Greek 10-year bond yield series. This choice is justified by the assumption that if during the post-crisis period contagion has emerged, then the first differences of Greek 10-year bond yields would be a significant predictor. Alternatively, if it tends to have little or no influence on the predicted series, then statistical insignificance of the respective estimates would be observed and consequently a pure ARMA model would be selected. By its essence, this approach enables detection and quantification of contagion.

Both types of models are tested up to 2nd order of AR and MA, as any higher order might result into fitting the noise in data and at the same time it is found that higher order models add no further predictive power as compared to simpler ones. The results would be interpreted as follows: if the selected model is pure ARMA, then there is no significant influence of the Greek bond market on the particularly studied European bond market and vice versa. Any discrepancies between the selected model for the first and for the second period would indicate presence of a structural break. Consequently, one could draw conclusions on whether convergence or divergence has occurred. Moreover, convergence would bring contagion after the Greek debt crisis.

In order to gain deeper knowledge on the studied pairwise dependencies, we apply multiscale analysis. In particular, we utilize continuous and discrete wavelet filtering so as to localize breaks and distinguish short-term changes and long-term shifts. Following (Aguiar-Conrara & Soares, 2014), we analyze co-movements through calculation of wavelet coherency:

$$R_{xy} = \frac{|S(W_{xy})|}{\left[S(|W_x|^2)S\left(|W_y|^2\right)\right]^{1/2}}, \quad (2)$$

where S is a smoothing operator in both time and scale, and given a time series $x(t) \epsilon L^2(\mathbb{R})$, its continuous wavelet transform with respect to the wavelet ψ and a family of wavelet daughters $\{\psi_{\tau,s};\ s, \tau \in \mathbb{R}, s \neq 0\}$: $\psi_{\tau,s} = \frac{1}{\sqrt{|s|}}\psi\left(\frac{t-\tau}{s}\right)$ is defined as

[1] For a detailed discussion the reader is referred to (Baillie, 1980).
[2] We use first differences as the raw data is nonstationary as explained in Section III.

$W_x = \int_{-\infty}^{\infty} x(t) \frac{1}{\sqrt{|s|}} \psi^* \left(\frac{t-\tau}{s}\right) dt$. Hence, the cross-wavelet transform of two time series $x(t)$ and $y(t)$ is defined as $W_{xy} = W_x W_y^*$. For empirical purposes we use the Morlet wavelet function. We estimate eq. (2) for each couple of EU-Greek first differenced 10-year bond yields through the Matlab toolbox of (Aguiar-Conrara & Soares, 2014).

The values of wavelet coherency R_{xy} are such that $0 \le R_{xy} \le 1$. The closer the value of R_{xy} to 1, the stronger is the co-movement between the time series $x(t)$ and $y(t)$. As might be seen the wavelet analysis provides time-frequency breakdown of the complicated dependencies contained in data, which is a major advantage. In particular, this continuous representation of studied dependencies enables identification of structural breaks.

In addition, we will extend this analysis through a close inspection of specific frequencies that are of interest. Considering bond markets, it is important to make difference between short-term movements, price corrections and long-term trends. Therefore, we would also apply discrete wavelet filtering. A common choice is the Haar “á trous” wavelet transform, introduced in (Zheng, et al., 1999). It decomposes the original sequence $\{x_t, t = 1, \dots, T\}$ with the application of the low-pass filter $\mathrm{g} = \left(\frac{1}{2}, \frac{1}{2}\right)$. As a result the following representation is delivered:

$$x_t = c_{J,t} + \sum_{j=1}^{J} w_j \qquad (3)$$

The smooth coefficients $\{c_J\}$ and the wavelet coefficients $\{w_j, = 1, \dots, J\}$ in Eq. (3) are calculated as follows:

$$c_{j,t} = \frac{1}{2}\left(c_{j-1,t-2^{j-1}} + c_{j-1,t}\right)$$

$$w_{j,t} = c_{j-1,t} - c_{j,t},$$

for $t = 1, \dots, T$ and $j = 1,2, \dots, J$, where $J < \log_2 T$.

This decomposition is found to be particularly useful for time series characterized by a complicated structure since eq. (3) breaks it down into simpler components, each characterized by a specific frequency. Higher values of j are associated with lower frequencies and vice versa. On the basis of (3) (Bogdanova & Ivanov, 2015) define a multiscale counterpart of the autocorrelation function. In (Bogdanova, et al., 2016) this concept is extended to multiscale cross-correlation matrix, defined as follows:

$$\mathrm{P}_{xy} = \begin{pmatrix} corr(y_t, w_{x1,(t-1)}) & corr(y_t, w_{x2,(t-1)}) & \cdots & corr(y_t, w_{xJ,(t-1)}) & corr(y_t, c_{xJ,(t-1)}) \\ corr(y_t, w_{x1,(t-2)}) & corr(y_t, w_{x2,(t-2)}) & \cdots & corr(y_t, w_{xJ,(t-2)}) & corr(y_t, c_{xJ,(t-2)}) \\ \dots\dots\dots\dots\dots\dots\dots & \dots\dots\dots\dots\dots\dots\dots & \cdots & \dots\dots\dots\dots\dots\dots\dots & \dots\dots\dots\dots\dots\dots\dots \\ corr(y_t, w_{x1,(t-S)}) & corr(y_t, w_{x2,(t-S)}) & \cdots & corr(y_t, w_{xJ,(t-S)}) & corr(y_t, c_{xJ,(t-S)}) \end{pmatrix} \qquad (4)$$

We estimate eq. (4) for each couple of EU-Greek first differenced 10-year bond yields, where the time series x_t corresponds to the first differences of Greek bond yields. P_{xy} is estimated over both pre- and post-crisis data though the source code associated with the paper of (Bogdanova, et al., 2016). Finally, we compare results and identify changes in short-term movements, price corrections as well as long-term shifts.

III. DATA AND RESULTS

1. Data[3]

The dataset consists of weekly observations on the 10-year bond yields of the five countries under study for the period spanning from January 2004 to October 2014, thus including 561 observations in total. The sub-periods are January 2004 – October 2009 and October 2009 – October 2014 and raw data is visualized at Figure 1.

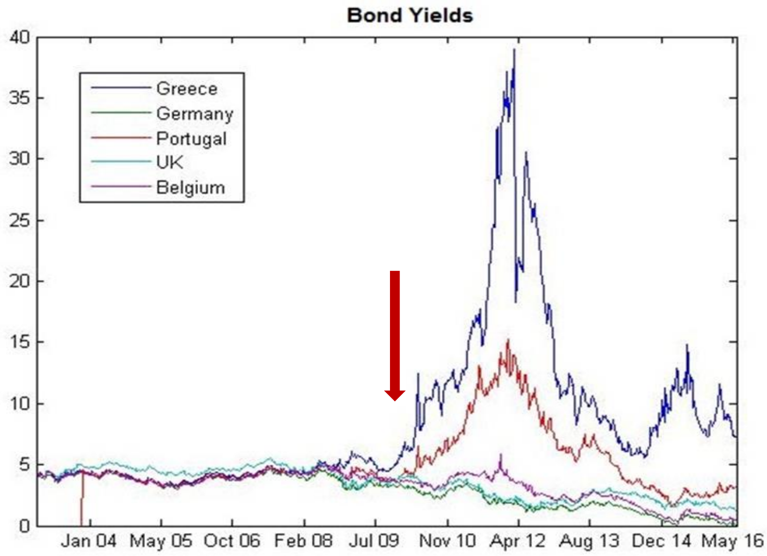


Figure 1: *10-year bond yields of Greece, Germany Portugal, the UK and Belgium.*

Looking at Figure 1, one could easily note that October 2009 is an appropriate date for splitting data, as the graph confirms presence of significant changes in all of the time series, probably driven by Papandreu's announcement that Greece's budget deficit will exceed 12% of the GDP, nearly double the original estimates (Anon., 2015). The high volatility and sharp changes in series evolvement during the second period also hints that the series might not be stationary, the latter finding being supported by the Augmented Dickey-Fuller test, reported in Table 1.

	Bond Yields				
	Greece	Germany	Portugal	UK	Belgium
Mean	8.49	2.77	5.19	3.50	3.29
StD	6.64	1.30	2.65	1.20	1.20
Skewness	2.24	-0.50	1.69	-0.27	-1.01
Kurtosis	8.17	1.93	5.26	1.65	2.88
ADF Stat	-1.27	-1.54	-0.81	-1.22	-1.32
ADF P-Value	(0.188)	(0.116)	(0.355)	(0.203)	(0.174)
JB Stat	1368.60	63.16	451.30	61.90	119.66
JB P-Value	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)

Table 1: *Descriptive statistics of studied bond yields.*

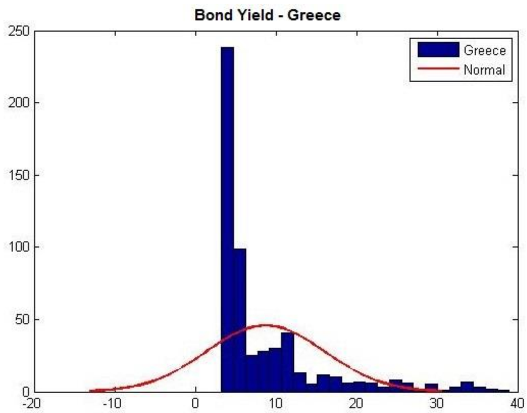


Figure 2: *Distribution of the Greek bond yield.*

[3] The data is taken from https://www.quandl.com/data/YC/GRC10Y-Greek-Government-10-Year-Bond-Yield and http://www.investing.com/.

1st Difference of Bond Yields					
	Greece	Germany	Portugal	UK	Belgium
Mean	0.00	-0.01	0.00	0.00	-0.01
StD	1.08	0.10	0.32	0.11	0.13
Skewness	-9.28	0.09	0.18	-0.05	-0.31
Kurtosis	197.65	3.50	15.12	4.31	23.35
ADF Stat	-30.49	-28.98	-24.78	-28.27	-29.36
ADF P-Value	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
JB Stat	1115161.08	8.38	4007.68	50.61	12091.11
JB P-Value	(0.001)	(0.019)	(0.001)	(0.001)	(0.001)

Table 2: *Basic statistics of the first difference of the bond yields.*

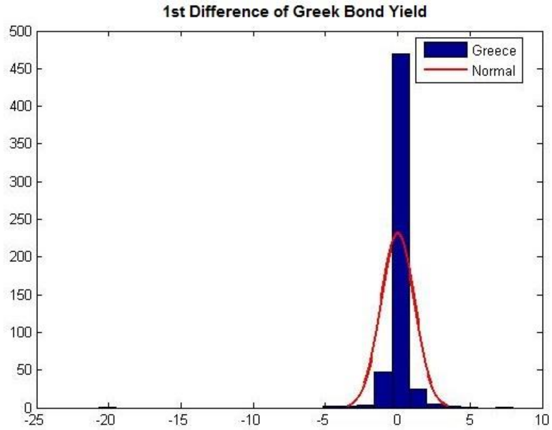


Figure 3: *Distribution of the first difference of the Greek bond yield.*

Table 1 and Table 2 summarize descriptive statistics of raw data and first differenced data. As might be further seen, the Jarque-Bera test confirms that series are not normally distributed, but are stationary. Figure 2 and Figure 3 show the distributions of the Greek bond yield and its first difference.

2. ARMA(X) analysis

After transforming the data, the next step is to inspect the autocorrelation function and the partial autocorrelation function of each time series. Figure 4 exhibits results for Greece.

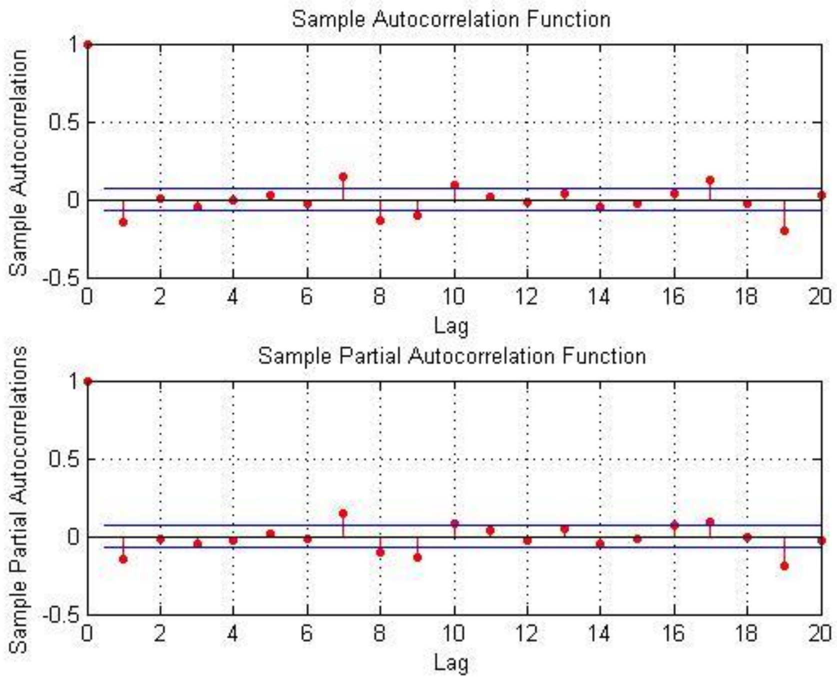


Figure 4: *Autocorrelation and partial correlation of the first difference of the Greek bond yield.*

We perform model selection on the basis of Akaike and Schwarz information criteria. Table 3 and 4 reveal the best models for each country, for both periods[4]. Each of them reaches the minimum result for AIC and BIC, and the residuals are white noise. The results should be interpreted thusly: for the period before October 2009 positive correlation was present in the movement between Germany and Greece, and Belgium and Greece. For the second sub-period no relationship in the development of the economies could be detected. On the other hand, the initial neutrality between Portugal and Greece has turned into positive correlation, hinting at the start of convergence. But at the same time this could be a sign of contagion. The model, however, cannot provide any further information on the question. For the UK series there has been no change concerning the relationship with Greece.

Before October 2009	
Germany	ARMAX(2,0)
Portugal	ARMA (1,1)
UK	ARMA (1,1)
Belgium	ARMAX(1,1)

Table 3: *Best models for Germany, Portugal, the UK and Belgium for the first sub-period.*

After October 2009	
Germany	ARMA (1,1)
Portugal	ARMAX(2,1)
UK	ARMA (2,2)
Belgium	ARMA (2,3)

Table 4: *Best models for Germany, Portugal, the UK and Belgium for the second sub-period.*

3. Multiscale analysis

A wavelet coherency graph for each country, paired with Greece, has been derived. It portrays the observed dependences in the time-frequency domain. Figure 5 shows the relationship between Greece and Belgium[5]. The red hues hint at a high degree of co-movement, while the blue ones reveal lack of any relationship. On the y axis the frequency of the relationship is indicated, while the x axis points at the time. The thick black curve (cone of influence) limits the real data from the extrapolated ones. Therefore, only the results inside the cone should be interpreted. The meaning of the graph is that for the period until June 2009 the two economies were closely moving together. After that a structural break took place (in the long-term frequencies), causing divergence in their further development.

Furthermore, the cross-correlation matrices confirm this result through the significant correlation coefficients (highlighted) and demonstrate that the long-term co-movement that once existed between the countries ceased in the second sub-period.

The interpretation of the correlation matrices is highly related to Dow Theory. Any correlation between the countries in the high-frequency range (w_1 and w_2) is a sign of short-term dependence. An example would be daily news that affects markets in the same direction. The mid-frequency range (w_3 and w_4) has to do with the price correction. There are the frequencies we track in order to confirm the presence of contagion. The last

[4] Please, refer to Appendix A for more details on the models.
[5] Please, refer to Appendix B for the graphs for the rest of the countries.

column in the matrices (c_4) is the long-term component that gives information about the fundamental relationship between the economies. Any difference in the significance of the coefficients in that column should be considered evidence of a structural change.

The results for Germany are almost identical as the ones for Belgium. An interesting observation is the UK, as there were some significant correlations with Greece in the mid-term range, which, however, vanished after the crisis. The outcome for Portugal is probably the most exciting, as the shift in the significant coefficients describes a decaying long-term relationship with Greece, but an evident presence of contagion, as most of the correlation coefficients are concentrated in the mid-term range[6].

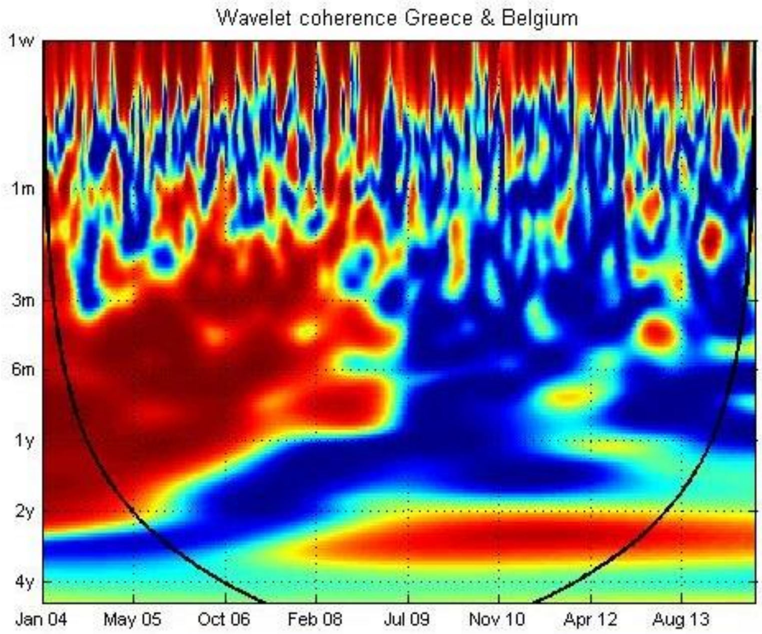


Figure 5: *Wavelet coherency between Belgium and Greece.*

	Correlation						Correlation				
	w_1	w_2	w_3	w_4	c_4		w_1	w_2	w_3	w_4	c_4
$t-1$	0.4936***	0.2424***	0.3492***	0.2449***	0.2461***	$t-1$	-0.0508	0.0598	0.0363	-0.0868	-0.0144
$t-2$	0.0879	0.0603	-0.0763	-0.0027	-0.1207**	$t-2$	-0.1506**	0.0493	-0.0168	0.0771	0.0106
$t-3$	-0.0805	0.0441	-0.0106	0.0528	0.0974	$t-3$	0.0715	0.0286	0.0035	-0.0299	-0.0143
$t-4$	-0.0077	-0.0544	-0.1042*	0.0563	-0.1532**	$t-4$	0.1170*	0.0556	0.0127	0.0814	0.0410
$t-5$	-0.0166	0.1817***	-0.0018	0.0336	0.1229**	$t-5$	-0.0059	-0.0403	-0.0067	-0.0509	-0.0224
$t-6$	0.0063	-0.0582	-0.1149*	0.0880	-0.1593***	$t-6$	-0.0133	-0.0701	0.0645	0.0112	-0.0061
$t-7$	0.1719***	-0.0748	0.0693	-0.0037	0.1035*	$t-7$	-0.0176	0.0257	-0.0851	0.0076	-0.0285
$t-8$	-0.0770	-0.0010	-0.0592	0.0757	-0.1298**	$t-8$	-0.0093	-0.0460	0.0755	-0.0164	0.0183
$t-9$	-0.0893	-0.1133*	-0.0218	-0.0255	0.0786	$t-9$	-0.0170	0.0741	-0.0867	-0.0101	-0.0099
$t-10$	0.0714	-0.0521	0.0261	0.0841	-0.1366**	$t-10$	-0.0697	0.0673	0.0502	0.0380	-0.0034
$t-11$	-0.0938	0.0908	0.0535	-0.0459	0.1345**	$t-11$	0.0892	-0.0751	-0.0153	-0.0263	0.0004
$t-12$	-0.0669	-0.0901	0.0852	0.0873	-0.1588***	$t-12$	0.0821	0.0551	0.0515	0.0392	-0.0168
$t-13$	0.1274**	0.0423	0.0538	-0.0293	0.1176*	$t-13$	-0.0540	-0.1179*	-0.0053	-0.0212	-0.0324
$t-14$	-0.0070	0.0016	0.1094*	0.0667	-0.1347**	$t-14$	0.0029	0.0296	-0.0486	0.0173	-0.0366
$t-15$	-0.0405	-0.0093	-0.0229	-0.0464	0.0839	$t-15$	-0.0900	0.0003	0.0513	0.0356	-0.0031
$t-16$	-0.0379	0.1008	0.1022*	0.0416	-0.1558**	$t-16$	-0.0083	0.0459	-0.0339	-0.0058	-0.0559
$t-17$	0.0095	-0.0009	0.0360	-0.0801	0.1103*	$t-17$	0.0634	0.0352	0.0294	0.0660	0.0056
$t-18$	0.0863	0.0895	0.0214	0.0566	-0.1770***	$t-18$	0.0565	-0.0536	0.0125	-0.0028	-0.0605
$t-19$	0.0101	0.0017	-0.0211	-0.0663	0.1150*	$t-19$	-0.0364	0.0524	-0.0101	0.0363	-0.0205
$t-20$	-0.0026	0.0137	0.0154	-0.0373	-0.1899***	$t-20$	-0.0383	-0.0723	-0.0142	0.0238	-0.0596

Table 5: *Correlation matrices for Belgium and Greece before the crisis (left) and after the crisis (right).*

IV. CONCLUSION

It might be summarized that both the classical and the novel methods provided similar results, proving that a combination of both approaches could help one reveal much more about the situation, thus ensuring robustness of results. The findings of ARMA(X) modelling are further elaborated on and explained with the introduction of multiscale analysis, which enhances identification of breaks and shifts in the long-term trends.

APPENDIX A: Selected ARIMA(X) models

ARIMAX(1,0,1) Model:

Conditional Probability Distribution: Gaussian

Parameter	Value	Standard Error	t Statistic
Constant	-0.00218559	0.00256844	-0.850938
AR{1}	0.129524	0.0392632	3.29885
MA{1}	-0.368853	0.0407092	-9.06067
Beta1	0.635311	0.0236136	26.9044
Variance	0.00451754	0.000257351	17.554

Model for Belgium, pre-crisis period

ARIMA(2,0,3) Model:

Conditional Probability Distribution: Gaussian

Parameter	Value	Standard Error	t Statistic
Constant	-0.00947026	0.00920142	-1.02922
AR{1}	0.912432	0.0596023	15.3087
AR{2}	-0.921508	0.0618577	-14.8972
MA{1}	-1.06399	0.0728089	-14.6135
MA{2}	1.03071	0.0912877	11.2908
MA{3}	-0.20889	0.046278	-4.51381
Variance	0.0226524	0.000941833	24.0514

Model for Belgium, post-crisis period

ARIMAX(1,0,0) Model:

Conditional Probability Distribution: Gaussian

Parameter	Value	Standard Error	t Statistic
Constant	-0.00397008	0.00578659	-0.686083
AR{1}	-0.178283	0.0662127	-2.69258
Beta1	0.145912	0.0407426	3.58131
Variance	0.0094036	0.000733291	12.8238

Model for Germany, pre-crisis period

ARIMA(1,0,1) Model:

Conditional Probability Distribution: Gaussian

Parameter	Value	Standard Error	t Statistic
Constant	-0.0155766	0.0116541	-1.33658
AR{1}	-0.864269	0.114773	-7.53022
MA{1}	0.804945	0.13776	5.84311
Variance	0.010736	0.000911582	11.7773

Model for Germany, post-crisis period

ARIMA(1,0,1) Model:

Conditional Probability Distribution: Gaussian

Parameter	Value	Standard Error	t Statistic
Constant	-0.00728456	0.011964	-0.608874
AR{1}	-0.747031	0.310213	-2.40812
MA{1}	0.712041	0.33124	2.14962
Variance	0.012564	0.000764976	16.4241

Model for the UK, pre-crisis period

ARIMA(2,0,2) Model:

Conditional Probability Distribution: Gaussian

Parameter	Value	Standard Error	t Statistic
Constant	-0.00921166	0.0152721	-0.60317
AR{1}	-0.366742	0.00727884	-50.3846
AR{2}	-0.94404	0.00782067	-120.711
MA{1}	0.352101	0.0181285	19.4225
MA{2}	1	0.0187771	53.2563
Variance	0.0112505	0.000978775	11.4945

Model for the UK, post-crisis period

ARIMA(1,0,1) Model:

Conditional Probability Distribution: Gaussian

Parameter	Value	Standard Error	t Statistic
Constant	-0.00252373	0.0113522	-0.222312
AR{1}	-1	0.00361139	-276.902
MA{1}	1	0.00893057	111.975
Variance	0.0105728	0.000589151	17.9459

Model for Portugal, pre-crisis period

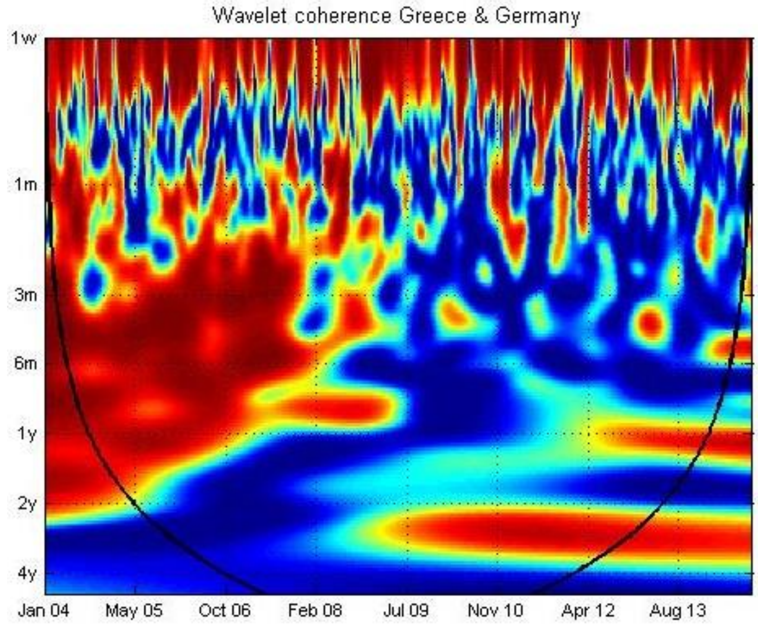
ARIMAX(2,0,1) Model:

Conditional Probability Distribution: Gaussian

Parameter	Value	Standard Error	t Statistic
Constant	-0.0020102	0.011839	-0.169794
AR{1}	0.564611	0.125758	4.48967
AR{2}	-0.204556	0.0544117	-3.75941
MA{1}	-0.615811	0.123135	-5.00111
Beta1	0.0495359	0.0159122	3.11308
Variance	0.207809	0.0107138	19.3964

Model for Portugal, post-crisis period

APPENDIX B: Wavelet coherency graphs and correlation matrices

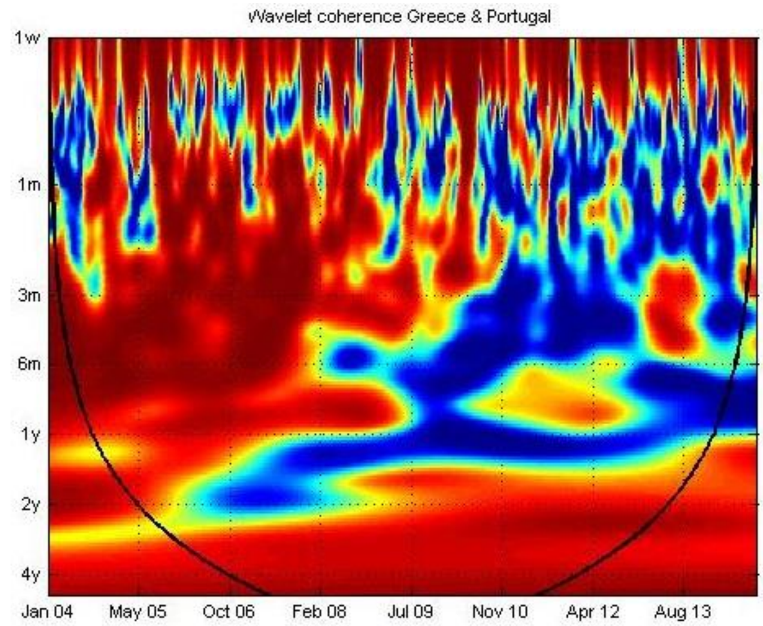


Wavelet coherency between Germany and Greece.

Correlation					
	w_1	w_2	w_3	w_4	c_4
$t-1$	-0.0003	0.0076	-0.1083	-0.0491	-0.1589
$t-2$	0.0174	0.0367	0.0923	-0.0958	0.0821
$t-3$	0.0264	-0.1265	-0.0567	0.0435	-0.1568
$t-4$	-0.0528	0.1703	0.0124	-0.1447	0.0937
$t-5$	-0.0413	-0.0894	-0.0792	0.0197	-0.1330
$t-6$	0.1413	0.0437	0.0167	-0.1573	0.1085
$t-7$	-0.1280	0.0813	-0.0570	0.0543	-0.0897
$t-8$	0.0166	-0.1100	-0.0484	-0.1845	0.1070
$t-9$	0.1683	0.0026	-0.0177	0.0380	-0.0853
$t-10$	-0.1134	0.0202	-0.1144	-0.1225	0.1342
$t-11$	-0.0924	-0.1256	0.0712	-0.0150	-0.1135
$t-12$	0.0515	0.0669	-0.1160	-0.0685	0.1467
$t-13$	0.0181	-0.0383	0.0547	-0.0021	-0.0780
$t-14$	0.0401	-0.0596	-0.1256	-0.0441	0.1297
$t-15$	-0.1229	0.0793	0.1214	-0.0376	-0.0766
$t-16$	-0.0359	-0.1001	-0.1110	-0.0123	0.1325
$t-17$	0.1745	0.0473	0.0662	-0.0328	-0.0755
$t-18$	-0.0531	-0.0822	-0.0218	0.0282	0.1553
$t-19$	-0.1128	0.0816	-0.0136	-0.0939	-0.1147
$t-20$	0.0014	-0.0530	-0.0149	0.0644	0.1867

Correlation					
	w_1	w_2	w_3	w_4	c_4
$t-1$	0.0084	0.0347	-0.0684	-0.0219	0.0813
$t-2$	0.0016	0.1245	0.1023	-0.0386	-0.0876
$t-3$	0.0247	-0.0107	-0.0291	-0.0975	0.1006
$t-4$	0.0864	0.0213	0.0884	-0.0353	-0.1151
$t-5$	-0.0107	-0.0378	-0.0722	-0.0402	0.1059
$t-6$	-0.0047	-0.0392	0.0415	-0.0842	-0.1104
$t-7$	-0.0185	-0.0428	-0.0257	0.0102	0.0832
$t-8$	-0.0487	0.0222	0.0888	-0.1433	-0.0859
$t-9$	-0.0050	-0.0565	0.0299	0.0270	0.0807
$t-10$	0.0478	0.1016	-0.0039	-0.1935	-0.0601
$t-11$	-0.0317	0.0555	-0.0788	0.0754	0.0637
$t-12$	-0.0154	0.0604	-0.0023	-0.2184	-0.0482
$t-13$	-0.0104	0.0490	-0.0028	0.1013	0.0619
$t-14$	0.1245	-0.1049	-0.0141	-0.2039	-0.0350
$t-15$	0.1301	-0.1037	0.0160	0.0511	0.0577
$t-16$	-0.1491	-0.0180	-0.1320	-0.1681	-0.0186
$t-17$	-0.1804	0.0003	-0.0265	0.0587	0.0491
$t-18$	0.0276	0.1028	-0.1620	-0.1045	0.0399
$t-19$	0.0867	0.0419	0.0260	0.1456	0.0594
$t-20$	0.0684	-0.0276	-0.1446	-0.1439	0.0443

Correlation matrices for Germany and Greece before the crisis (left) and after the crisis (right).

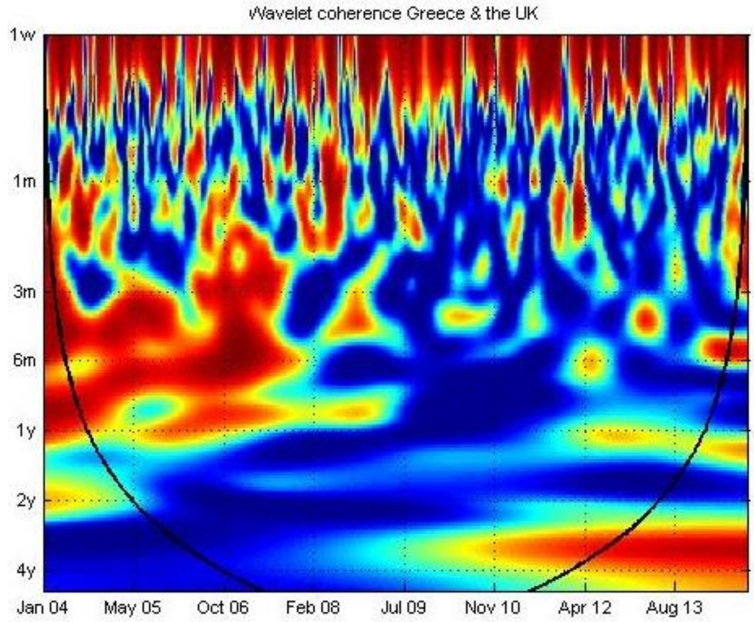


Wavelet coherency between Portugal and Greece.

	Correlation				
	w_1	w_2	w_3	w_4	c_4
$t-1$	-0.0357	-0.0398	-0.0583	0.0623	-0.0694
$t-2$	0.0396	-0.0134	-0.0021	-0.0151	0.0289
$t-3$	-0.0663	0.0804	-0.0698	0.1572	-0.0760
$t-4$	-0.1283	0.1554	-0.0522	-0.0248	0.0391
$t-5$	0.1165	-0.0315	-0.0184	0.1675	-0.0846
$t-6$	0.1998	-0.0412	0.0538	-0.0102	0.0528
$t-7$	-0.0607	-0.0848	0.0047	0.0631	-0.0807
$t-8$	-0.0668	-0.1365	-0.0682	-0.0187	0.0189
$t-9$	-0.0368	0.0207	0.0568	0.0700	-0.0750
$t-10$	-0.1224	0.0930	-0.0448	-0.0010	0.0763
$t-11$	0.0230	-0.0093	0.1414	0.0644	-0.0831
$t-12$	0.1315	0.0442	-0.0167	0.0480	0.0633
$t-13$	0.0184	-0.0357	0.1464	-0.0109	-0.0900
$t-14$	-0.0168	-0.0705	-0.0389	-0.0061	0.0306
$t-15$	-0.0722	0.1138	0.0911	-0.0532	-0.1018
$t-16$	-0.0399	-0.0479	0.0579	-0.0473	0.0579
$t-17$	0.0804	0.1341	0.0343	-0.0172	-0.1167
$t-18$	0.0042	-0.0173	0.0709	-0.0266	0.0683
$t-19$	0.0619	-0.0159	0.0123	-0.1010	-0.1443
$t-20$	-0.0306	0.0268	0.0516	-0.0100	0.0756

	Correlation				
	w_1	w_2	w_3	w_4	c_4
$t-1$	0.1139	0.0615	0.0703	-0.0796	0.0624
$t-2$	0.0607	-0.0595	0.0513	0.1460	0.0728
$t-3$	0.0188	0.0482	-0.1242	-0.0747	0.0008
$t-4$	-0.0919	0.0240	0.0187	0.1475	0.0380
$t-5$	-0.0613	-0.0031	0.0444	-0.1103	0.0094
$t-6$	0.0374	0.0250	0.1195	0.1136	0.0696
$t-7$	0.1733	-0.1699	0.0256	-0.0505	0.0061
$t-8$	0.0508	-0.0480	0.0691	0.1085	0.0485
$t-9$	-0.2899	0.0472	-0.0633	-0.0232	-0.0017
$t-10$	-0.1032	0.0833	0.0271	0.0741	0.0214
$t-11$	0.1613	0.1122	-0.0069	0.0897	0.0445
$t-12$	0.0858	0.0994	0.0692	0.0037	0.0408
$t-13$	0.0366	-0.0267	-0.1093	0.0134	-0.0095
$t-14$	0.0521	-0.0176	0.0298	-0.0443	-0.0082
$t-15$	-0.0722	-0.0168	-0.1023	0.0826	-0.0039
$t-16$	-0.0462	-0.0501	0.0747	-0.0756	0.0043
$t-17$	0.0692	-0.0861	-0.0425	0.1273	0.0169
$t-18$	0.0148	-0.0087	0.0768	-0.0796	0.0095
$t-19$	-0.0904	-0.0892	0.0450	0.0775	-0.0018
$t-20$	-0.0560	0.1018	0.0270	-0.0888	-0.0182

Correlation matrices for Portugal and Greece before the crisis (left) and after the crisis (right).



Wavelet coherency between the UK and

Correlation					
	w_1	w_2	w_3	w_4	c_4
$t-1$	0.0463	-0.0114	-0.1017	0.0140	-0.0103
$t-2$	0.0206	0.1177	0.0265	-0.0072	0.0105
$t-3$	-0.0516	-0.0264	-0.1270	0.1219	-0.0335
$t-4$	0.0529	0.0567	0.0075	-0.0713	-0.0010
$t-5$	0.0418	-0.0245	-0.1131	0.1207	-0.0262
$t-6$	0.0280	-0.0208	-0.0801	-0.0132	-0.0247
$t-7$	-0.0667	-0.0201	-0.0682	0.1113	-0.0147
$t-8$	-0.0347	-0.0520	-0.0049	-0.0371	-0.0247
$t-9$	0.0598	-0.0834	0.0324	0.1306	-0.0238
$t-10$	0.0139	-0.0394	0.0082	-0.0560	0.0095
$t-11$	-0.0793	-0.1119	0.1409	0.1079	-0.0357
$t-12$	-0.0619	0.0581	-0.0558	-0.0020	-0.0025
$t-13$	-0.0122	0.0335	0.1210	0.1144	-0.0275
$t-14$	0.0578	-0.0126	0.0557	-0.0281	0.0196
$t-15$	-0.0443	0.1527	0.1277	0.0596	-0.0407
$t-16$	0.0231	-0.0727	0.0152	-0.1039	0.0188
$t-17$	0.1475	0.0646	0.0589	0.0560	-0.0728
$t-18$	-0.1229	0.0795	-0.0537	-0.0209	0.0362
$t-19$	-0.0504	0.0122	0.0209	-0.0507	-0.1079
$t-20$	0.1286	0.0056	0.0026	0.0105	0.0575

Correlation					
	w_1	w_2	w_3	w_4	c_4
$t-1$	0.0082	0.1055	-0.0584	0.0180	0.0182
$t-2$	-0.0467	0.0401	0.0588	0.0369	-0.0710
$t-3$	0.1123	-0.0591	-0.0477	-0.0051	0.0205
$t-4$	0.0318	0.0721	0.0214	0.0552	-0.0571
$t-5$	-0.0794	-0.1402	0.0175	0.0005	-0.0056
$t-6$	0.0401	0.0433	-0.0479	0.0599	-0.1046
$t-7$	-0.0372	-0.0532	0.0680	0.0448	0.0318
$t-8$	-0.0082	0.0186	-0.0256	-0.0028	-0.1201
$t-9$	-0.0484	0.0913	-0.0051	0.1150	0.0224
$t-10$	0.0390	-0.0414	-0.0188	0.0003	-0.0970
$t-11$	0.0574	0.0964	0.0035	0.0615	0.0245
$t-12$	-0.0429	-0.0781	0.0973	-0.0497	-0.1389
$t-13$	0.0662	-0.0171	-0.0569	0.0551	0.0025
$t-14$	-0.0132	-0.0305	0.0862	-0.0046	-0.1019
$t-15$	-0.0503	-0.0403	-0.0171	-0.0010	-0.0026
$t-16$	-0.0437	0.1004	0.0025	0.0332	-0.1197
$t-17$	0.0097	-0.0648	0.0912	-0.0038	0.0046
$t-18$	0.0565	0.0753	0.0250	0.0222	-0.1279
$t-19$	-0.0273	-0.0108	0.0344	0.0289	-0.0021
$t-20$	0.0761	0.0192	-0.1480	-0.0015	-0.1090

Correlation matrices for the UK and Greece before the crisis (left) and after the crisis (right).

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