

*José Alberto Fuinhas* \*, *António Cardoso Marques* \*

## **DIFFERENT MEASURES OF VOLATILITY: THE HYPOTHESIS OF OUTPUT COMPOSITION IN PORTUGAL<sup>1</sup>**

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This paper focuses on analyzing the impact of the consequences of monetary union on GDP volatility in Portugal. Using quarterly data from 1978:01 to 2009:04, we test the output composition effect and the correlation effect through three alternative approaches of volatility: year on year, quarter on quarter and the value of output gap. Results support the presence of the composition effect. Overall, the average covariance has played a relevant role in lowering volatility. Evidence also indicates that there is a regime shift near the years 1992-3, while both European Union membership and participation in the euro area contribute towards smoothing the economy. The decreasing path of volatility was slightly reversed after the country became a euro area member.

**Keywords:** macroeconomic volatility, output composition effect, correlation effect

### **1. INTRODUCTION**

The analysis of volatility of the aggregate economic activity is often linked to the context of its persistent decline, as pointed out by Davis and Kahn (2008) and by Enders and Ma (2011). Both the start and the structure of the shrink of volatility were different across the most advanced economies and have been so widespread and persistent that this general phenomenon, which started in the early 1980s, was called the Great Moderation by Stock and Watson (2002). At first glance, this phenomenon was the object of USA analysis (Kim and Nelson, 1999; and McConnell and Perez-Quiros, 2000), but was subsequently extended to the broader context of OECD countries.

The fall in volatility has been mainly identified as trending down rather than dropping (Blanchard and Simon, 2001; and Davis and Kahn, 2008).

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\* University of Beira Interior, Department of Management and Economics Covilhã, Portugal

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Meanwhile some papers have found structural breaks in the volatility of American output (Kim and Nelson, 1999; and McConnell and Perez-Quiros, 2000). In fact, the literature recognizes two main points of view, namely, whether the fall in volatility results from a long period of luck in the form of soft shocks and could therefore be reversed quickly or is, on the other hand, ascribable to changes in the structures of the economies and could be considered permanent.

In contrast to the case of the United States, the research of macroeconomic volatility in Europe has been scarcely studied. Buch et al. (2004), Cabanillas and Ruscher (2008) and Aßmann et al. (2009) are exceptions. This scarcity, together with the lack of robust evidence concerning the roots of volatility behaviour motivates our analysis. We focus on three less studied aspects: (i) the robustness of volatility to its calculus; (ii) the effect of European Union (EU) membership and subsequent participation in the euro area on volatility; and (iii) the possibility of changes in GDP components, i.e. changes in shares and correlation between components which affect the processes generating the volatility.

This paper provides new evidence on this issue: firstly, it includes the Portuguese case in the literature on Europe; secondly, it estimates three distinct approaches to the calculus of volatility; and thirdly, it tests the hypothesis of output composition. The Portuguese reality is poorly studied, but it has several characteristics of interest concerning the study of volatility: (i) it has credible available data for a long time span; (ii) it became a member of the EU (in 1986) near the time mostly accepted to be the beginning of Great Moderation; and (iii) being a small economy, it is expected to be deeply conditioned by its integration in the euro area (year 1999). Meanwhile, lengthy stagnation and structural handicaps make it difficult for Portugal to accomplish the requirements within the EU. In such an environment, we expect the economy to be better able to absorb outside shocks. Mild shocks must be translated into less volatility. This mix of characteristics made Portugal an interesting case study.

The results reveal that: (i) volatility is sensitive to the method of calculus; (ii) the participation in the euro area suggests a structural break; and (iii) the composition changes, both in shares and in correlations, have played a role in the Portuguese slowdown of volatility. The remainder of the paper is organized as follows: section 2 debates the hypothesis of output composition; section 3 exposes data, the different approaches to output volatility, and the methodology of volatility calculus; section 4 describes and

discusses the Portuguese output volatility process, looking at the contribution of GDP components; and section 5 presents concluding remarks.

## **2. VOLATILITY AND THE HYPOTHESIS OF OUTPUT COMPOSITION**

Volatility is generally a measure for the variation of series over time and is a noteworthy phenomenon in macroeconomics. There is even a large literature devoted to studying the interaction between volatility and economic growth. A good survey on this relationship was undertaken by Fang and Miller (2008). While volatility is not directly observable, it is possible to identify some stylized facts: (i) volatility evolves over time in a continuous way – volatility jumps are uncommon; (ii) volatility does not diverge to infinity – volatility varies inside a limited range of values; and (iii) volatility is a crude measure of risk/opportunities – volatility seems to interact with GDP growth itself. Here, volatility means the standard deviation of underlying GDP growth rates, i.e. it is a measure of variation of the GDP growth rates over time.

The decline in volatility has been explained by five main competing theories, which are nothing more than possible causes for the decline in volatility. First, innovations and structural changes in inventory management (Summers, 2005). Kahn et al. (2002) consider that just-in-time has significantly smoothed output. The best management of inventories results in a decline in the weight of inventories in sales, principally for durable goods. Second, changes in monetary policy carried out by Volcker and Greenspan have probably reduced the effect of economic fluctuations (Clarida et al., 2000; and Boivin and Giannoni, 2006). The Federal Reserve's only slight reaction to output fluctuations relative to inflation may have led to more stable monetary policy and more stable output growth. Third, Stock and Watson (2002) point out that the hypothesis of "good luck", i.e. smaller exogenous shocks, was the source of increased stability. This hypothesis presumes that the nature of the innovations themselves might have changed, becoming smaller and, in some cases such as oil shocks, less frequent (Ahmed et al., 2004). This explanation assumes a generalized reduction in all sorts of shocks, particularly in high frequency innovations. If good luck were the principal source of stability, then policymakers should be prepared for a return to the bad times of the past (Cabanillas and Ruscher, 2008).

Furthermore, the prominence of the hypothesis of good luck in literature leaves relatively little scope for changes in economic policies, particularly monetary policy, and for structural changes in the economies, as the determinant sources of stabilization. Fourth, increased global integration and several innovations occurred in financial market regulations (Dyanan et al., 2006). Changes in government policy (e.g. the demise of Regulation Q) and several advances in loan markets and lending practices improved the capacity of firms and households to borrow. Fifth, changes in the workforce age composition, within the labour market, may have reduced economic fluctuations (Jaimovich and Siu, 2009). Hours and wages are more volatile over the business cycle for young workers. In other words, the employment and hours worked by the young fluctuate much more over the business cycle than those of older workers, which contributes to stabilizing the economy.

The presence of a multiplicity of explanations is a good indicator that there is no apparent consensus as to the root cause of the stabilization (e.g. Enders and Ma, 2011). Nevertheless, the review of literature for the United States suggests two main conclusions: (i) the decline in output volatility probably reflects a multiplicity of factors; and (ii) a central role has been attributed to the hypothesis of good luck. As Bernanke (2004) pointed out, these explanations are not mutually exclusive. However, the relative weight of the causes indicated as the source of less volatility has several implications for economic policy. If the main cause of less volatility results from improvements in monetary policy, then this policy should be preserved. Nevertheless, if the low level of volatility results from structural changes, for example, in how inventories of goods and raw materials are managed, then policy must improve the mood of flexibility and innovation.

Some literature has investigated the extent to which the decline in macroeconomic volatility has encompassed both the disaggregated components of output and the industry classifications such as manufacturing (Stock and Watson, 2002; Kim et al., 2004). Besides the five possible causes suggested above, a way to learn more about the sources of the decline in output growth volatility is to divide GDP into its main components. Another way is to look for the traditional sources of GDP growth, such as total factor productivity, labour and capital. By examining their behaviour, one can try to explain the volatility of GDP as a whole. In line with most of the literature, we opt for the first way. Statistically speaking, a volatility reduction in aggregate real GDP can arise from three sources: (i) greater within-components stability; (ii) a shift in component shares to less volatile ones; and (iii) changing covariance between components. Actually, in this

work, we will focus on the output composition effect, which is conditional on the assessment of the Portuguese economic integration process.

To appreciate the shift in component shares (output composition effect), we can draw a comparison between the actual series of GDP and the counterfactual series, i.e. series constructed making the shares of their components constant at their value of the first five years of our sample. The distance between the counterfactual measure of volatility and the actual one gives an indication of the size of the composition effect.

The volatility of GDP growth depends on the volatility of its individual components and on their co-movements. *Ceteris paribus*, a decrease in the co-movements (correlation effect) between GDP components will entail a decrease in the volatility of GDP when correlation between volatility of its individual components is positive, and will lead to an increase in volatility when the correlations are negative. To check the magnitude of this correlation effect, we can compute a counterfactual series which is estimated as a measure of the volatility of GDP, assuming that all pair correlation coefficients between GDP components are held constant at their value of the first twenty quarters of our sample. The distance between actual and counterfactual series gives an indication of the size of the correlation effect.

### 3. DATA AND METHODOLOGY

The raw data comes from the Portuguese Central Bank. We use quarterly series from 1978:01 to 2009:04. To preserve the additivity property of data, GDP components were deflated by the GDP deflator. To calculate the potential growth we use the Hodrick-Prescott filter with  $\lambda=1600$ . Furthermore, the Hodrick-Prescott filter reveals the interesting property that the filtered aggregate is equal to the sum of its filtered components.

A special feature of GDP growth volatility is that it is not observable. The stylized facts are basically valid for approaches to volatility based on the standard deviation of year on year changes in the variables considered. Other types of indicators could, however, be constructed and stylized facts must be confronted with these alternative volatility indicators and tested to see whether they pass the robustness test of the choice of measurement.

To analyze the possible sensitivity of the measurement issues, we discuss three alternative approaches, which do not necessarily draw the same picture. The first one, the most commonly used in literature, is the standard deviation of the year on year (YY) GDP growth rates. The second one is a simple

variation of the basic measure, namely the standard deviation of the quarter on quarter (QQ) GDP growth rates. The third one is the standard deviation of the value of the output gap (OG). The latter measure tries to capture the idea that a long period of stable, but sluggish growth away from potential (a rather frequent occurrence in several countries) is not necessarily a sign of low volatility, although it will be associated with a low standard deviation of growth. Some authors (e.g. Cabanillas and Ruscher, 2008) prefer to use the absolute value of output gap. We will work upon an alternative measure of output gap allowed by the use of the Hodrick-Prescott filter. In this way, one captures another dimension of the calculus of volatility – the relative deviations to the trend (given that the variables are in logs). In short, we are interested in a measure of “relative” volatility. Another candidate is the volatility obtained using GARCH-type models (generalized autoregressive conditional heteroskedastic), but for reasons of scope and space, this will not be analyzed.

Since volatility is calculated as the standard deviation, it is of paramount importance to define what number of observations (window) should be considered. For reasons of comparability with most empirical work (e.g. Blanchard and Simon, 2001 and Cabanillas and Ruscher, 2008), we compute standard deviations by using a rolling window of twenty quarters. Therefore, the statistic reported for  $t$  is the estimated standard deviation over  $t-19$  quarters. We use the same time length for all calculus of volatility to preserve “some” comparability among estimates.

The effect of output composition on volatility involves what is known as an index-like problem. The volatility dynamics of GDP are the joint result of their components’ volatility dynamics and of changes in GDP composition. For this reason, by making the share of GDP components fixed, we can identify the contribution of the components’ volatility to GDP volatility; and if we make components’ volatilities fixed, we can identify the contribution of output composition changes to the change in GDP volatility. To separate these two effects, we compute a counterfactual series for GDP growth, obtained by holding each components’ share constant, and then compare the output volatility schedule obtained using this counterfactual series with that obtained using the original series.

There are many approaches to computing of constant shares. Specifically, McConnell and Perez-Quiros (2000) compute their counterfactual series holding each sector’s share constant at its sample-wide average; Blanchard and Simon (2001) use the 1947 shares and Stock and Watson (2002) use the 1965 shares. Since the actual and the counterfactual series look very similar

to each other, they conclude that composition effects have been of little importance, if any, for the decline in output volatility. We opt to use the first twenty quarters of data.

The fixed-weight GDP is calculated as the sum of the year on year growth rates of the GDP components, weighted by their average shares in the level of GDP for the first twenty quarters available. When the share of the component in GDP is not subject to any drift, the actual contribution to GDP growth is used.

The variance of GDP growth is the sum of the variance of its components, measured in contributions to GDP growth ( $Y_i$ ) and of all the pair covariance between these components, again measured in contributions to GDP growth and multiplied by 2. Formally, if

$$GDP = \sum_{i=1}^n GDP_i \quad (1)$$

with  $i$  = private consumption, public consumption, investment, inventories, and net exports. GDP growth (for  $i$  component at time  $t$ ) is defined as:

$$RGDP_{i,t} = \frac{GDP_{i,t} - GDP_{i,t-1}}{GDP_{i,t-1}}. \quad (2)$$

The aggregate GDP growth rate at time  $t$  is:

$$RGDP_t = \sum_{i=1}^n X_{i,t-1} \cdot RGDP_{i,t}, \quad (3)$$

with  $n$  being the number of components considered lagged once,

$$X_{i,t} = \frac{GDP_{i,t}}{GDP_t}, \text{ and } \sum_{i=1}^n X_{i,t} = 1.$$

The variance of GDP growth is computed as:

$$\sigma_{GDP}^2 = \sum_{i=1}^n X_i^2 \sigma_i^2 + \sum_{i=1}^n \sum_{\substack{j=1 \\ j \neq i}}^n X_i X_j \sigma_{ij} \quad (4)$$

where the  $\sigma_i^2$  means the variance of component  $i$ ,  $\sigma_{ij}$  means the covariance between components  $i$  and  $j$ ,  $\sum_{i=1}^n X_i^2 \sigma_i^2$  means the average variance, and  $\sum_{i=1}^n \sum_{\substack{j=1 \\ j \neq i}}^n X_i X_j \sigma_{ij}$  means the average covariance. The covariance is the value

of the product of two different deviations and, as such, it can be positive or negative. It will be larger when the outcomes for each variable occur together. This will result in a larger value for covariance and a larger value for the total variance. Thus, the covariance is a measure of how the contributions to growth of GDP move together.

Letting,

$$Y_{i,t} = X_{i,t-1} \cdot RGDP_{i,t}, \quad (5)$$

then:

$$\sigma_{GDP}^2 = \sum_{i=1}^n \sigma_i^2 + \sum_{i=1}^n \sum_{\substack{j=1 \\ j \neq i}}^n \sigma_{ij}. \quad (6)$$

The covariance between two GDP components depends on their correlation but also on their respective standard deviations. Formally:

$$\sigma_{ij} = \rho_{ij} \times \sigma_i \times \sigma_j, \quad (7)$$

where the  $\rho_{ij}$  denotes the correlations between components  $i$  and  $j$ . The variance of GDP is recalculated by holding all the pairs of  $\rho_{ij}$  coefficients constant. We do not make the usual seasonal adjustment of series to preserve their property of additivity. This is required to build the analysis of constant shares and constant correlations. For that purpose, we create routines in the econometric software RATS.

To assess the effects of both changes in shares and correlations of GDP components on the volatility of GDP growth, we use two approaches to evaluate the adherence of observed and counterfactual values: (i) graphical analysis; and (ii) several quantitative indicators of the goodness-of-fit measure. Indeed, we made use of these two approaches because it is generally agreed that purely qualitative visual comparisons of model predictions for data are insufficient (e.g. Smith and Rose, 1995). In order to compare the observed and counterfactual values, we can make use of linear regression. As with any regression approach, the degree to which the data evolved together should be evaluated both graphically and statistically. Thus, we regress what was observed on the counterfactual values:

$$y_t = \alpha + \beta y_t^c + \varepsilon_t, \quad (8)$$



where  $y_t$  is the value of observed data,  $y_t^c$  are the counterfactual values and  $\varepsilon_t$  is the error term. The equation (8) could be used to assess whether the observed and the counterfactual values are statically equivalent. When  $\beta = 1$  and  $\alpha = 0$ , then there is a perfect fit. To do that, we follow two sequential steps. First, we test whether the observed and counterfactual values vary consistently together, applying a Wald test with the null hypothesis  $H_0 : \beta = 1$ . When  $H_0$  is not rejected, we can conclude that the slope ( $\beta$ ) is not statistically different from one, and then the estimate of  $\alpha$  is  $\bar{y} - \bar{y}^c$ . Second, once the same slope is accepted, we test whether the values have the same intercept by applying a Wald test with the null hypothesis  $H_0 : \alpha = 0$ . The non rejection of  $H_0$  indicates that the observed and counterfactual mean are the same, and consequently no bias is present (i.e.,  $\bar{y} - b\bar{y}^c$  is zero, where  $b$  is the estimate of  $\beta$ ). It is worth noting that the applicability of these tests requires that the regression satisfies the assumptions of normality, homogeneity of variance, and independence. In other words, if both null hypotheses are not rejected, the counterfactual values are not distinguishable from the observed values, given the variation in the observed data.

We can interpret the adherence of counterfactual to observed data graphically. Indeed, the graphical analysis allows a good picture of the decomposition into components corresponding to degree of association (high positive correlation), accuracy (no bias), and precision (low variance). By plotting the observed against the counterfactual data, if counterfactual are similar to the observed values then: (i) the points would be nearly a straight line – near unitary slope; (ii) the points would go through the origin – no bias as the series has analogous means; and (iii) the dispersion of points around the regression line would be small – high correlation between counterfactual and observed values revealing low unexplained variation.

Beyond the primary analysis of the goodness-of-fit, we made several diagnostic analyses such as: (i) correlation; (ii) mean error; (iii) mean absolute error; (iv) root mean square error; (v) mean square error; (vi) mean percentage error; (vii) mean absolute percentage error; (viii) root mean square percentage error; (ix) Theil inequality measure; and (x) Theil's bias, variance and covariance proportions. Mean percentage error, mean absolute percentage error, and root mean square percentage error are defined only if the actual series is positive throughout the range. They are also all defined as decimals, not true percentages.

Let  $T$  mean the first observation of volatility available and  $h$  the last one. The reported error statistics are computed, as follows, for mean error (9), mean absolute error (10), mean squared error (11), root mean squared error (12), mean percentage error (13), mean absolute percentage error (14), root mean squared percentage error (15), and Theil inequality measure (17):

$$\text{Mean error} \quad \sum_{t=T+1}^{T+h} (y_t - y_t^c) / h \quad (9)$$

$$\text{Mean absolute error} \quad \sum_{t=T+1}^{T+h} |y_t - y_t^c| / h \quad (10)$$

$$\text{Mean squared error} \quad \sum_{t=T+1}^{T+h} y_t (y_t - y_t^c)^2 / h \quad (11)$$

$$\text{Root mean squared error} \quad \sqrt{\sum_{t=T+1}^{T+h} (y_t - y_t^c)^2 / h} \quad (12)$$

$$\text{Mean percentage error} \quad \sum_{t=T+1}^{T+h} \left( \frac{y_t - y_t^c}{y_t} \right) / h \quad (13)$$

$$\text{Mean absolute percentage error} \quad \sum_{t=T+1}^{T+h} \left| \frac{y_t - y_t^c}{y_t} \right| / h \quad (14)$$

$$\text{Root mean squared percentage error} \quad \sqrt{\sum_{t=T+1}^{T+h} \left( \frac{y_t - y_t^c}{y_t} \right)^2 / h} \quad (15)$$

$$\text{Theil inequality measure} \quad \frac{\sqrt{\sum_{t=T+1}^{T+h} (y_t - y_t^c)^2 / h}}{\sqrt{\sum_{t=T+1}^{T+h} y_t^2 / h + \sum_{t=T+1}^{T+h} y_t^{c2} / h}} \quad (16)$$

The first four forecast error statistics depend on the scale of the dependent variable. These should be used as relative approaches to compare forecasts for the same series across different models; the smaller the error, the better the forecasting ability of that model according to that criterion. The remaining statistic is scale invariant. The Theil inequality measure always lies between zero and one, where zero indicates a perfect fit. The

Theil's U statistic is a ratio of the root mean square error for the model to the root mean square error for a "no change" forecast. Indeed,

$$\sqrt{\sum_{t=T+1}^{T+h} (y_t - y_0)^2 / h}, \quad (17)$$

where  $y_0$  is the "naive" or flat forecast – simply the value of the dependent variable at the period T. This is a convenient measure because it is independent of the scale of the variables. Theil's U (18) and Theil's relative U (19):

$$\text{Theil's U} = \frac{\sqrt{\sum_{t=T+1}^{T+h} (y_t - y_t^c)^2 / h}}{\sqrt{\sum_{t=T+1}^{T+h} (y_t - y_0)^2 / h}}, \quad (18)$$

$$\text{Theil's relative U} = \frac{\sqrt{\sum_{t=T+1}^{T+h} \left( \frac{y_t - y_t^c}{y_t} \right)^2 / h}}{\sqrt{\sum_{t=T+1}^{T+h} \left( \frac{y_t - y_0}{y_t} \right)^2 / h}}. \quad (19)$$

The mean squared forecast error can be decomposed as:

$$\sum (y_t - y_t^c)^2 / h = \left( \left( \sum y_t^c / h \right) - \bar{y} \right)^2 + (s_y - s_y^c)^2 + 2(1 - r) s_y s_y^c, \quad (20)$$

where  $\sum y_t^c / h$ ,  $\bar{y}$ ,  $s_y^c$ ,  $s_y$ , are the means and (biased) standard deviations of  $y_t^c$  and  $y$ , and  $r$  is the correlation between  $y$  and  $y_t^c$ . The approaches of bias proportion (21), variance proportion (22) and covariance proportion (23) are defined as:

$$\text{Bias proportion} = \frac{\left( \left( \sum y_t^c / h \right) - \bar{y} \right)^2}{\sum (y_t - y_t^c)^2 / h}, \quad (21)$$

$$\text{Variance proportion} \quad \frac{(s_y - s_{y^c})^2}{\sum (y_t - y_t^c)^2 / h}, \quad (22)$$

$$\text{Covariance proportion} \quad \frac{2(1-r)s_y s_{y^c}}{\sum (y_t - y_t^c)^2 / h}. \quad (23)$$

The bias proportion tells us how far the mean of the counterfactual is from the mean of the observed series. The variance proportion reveals how far the variation of the counterfactual is from the variation of the observed series. The covariance proportion approaches the remaining unsystematic errors. Note that the bias, variance, and covariance approaches add up to one. If the adhesion is “good”, the bias and variance proportions should be small so that most of the bias should be concentrated on the covariance proportions.

#### 4. RESULTS AND DISCUSSION

This section presents the results of three approaches to volatility using quarterly data, namely the contributions of components, in percentage, to YY GDP growth, to QQ GDP growth rate annualized, and to OG.

We start by showing the basic properties of growth (see table A1 for the summary statistics of raw data). Figure 1 shows the behaviour path of growth for the three approaches under analysis. The patterns of growth consistently revealed pronounced cyclical behaviours and a visible decreasing trend.

Figure 2 shows the standard of deviation of output growth for a 5-year window. By comparing the volatility with output growth, such as expected, we observe the preservation of cyclical behaviour. The volatility of output growth seems to decline substantially after the mid 1990s, and reached a historical low mark around year 2000. After the early 2000s, volatility appears to be upward.

Table 1 displays the standard deviation of the contributions of GDP components to YY, QQ and OG for the period 1979:01 to 2009:04.

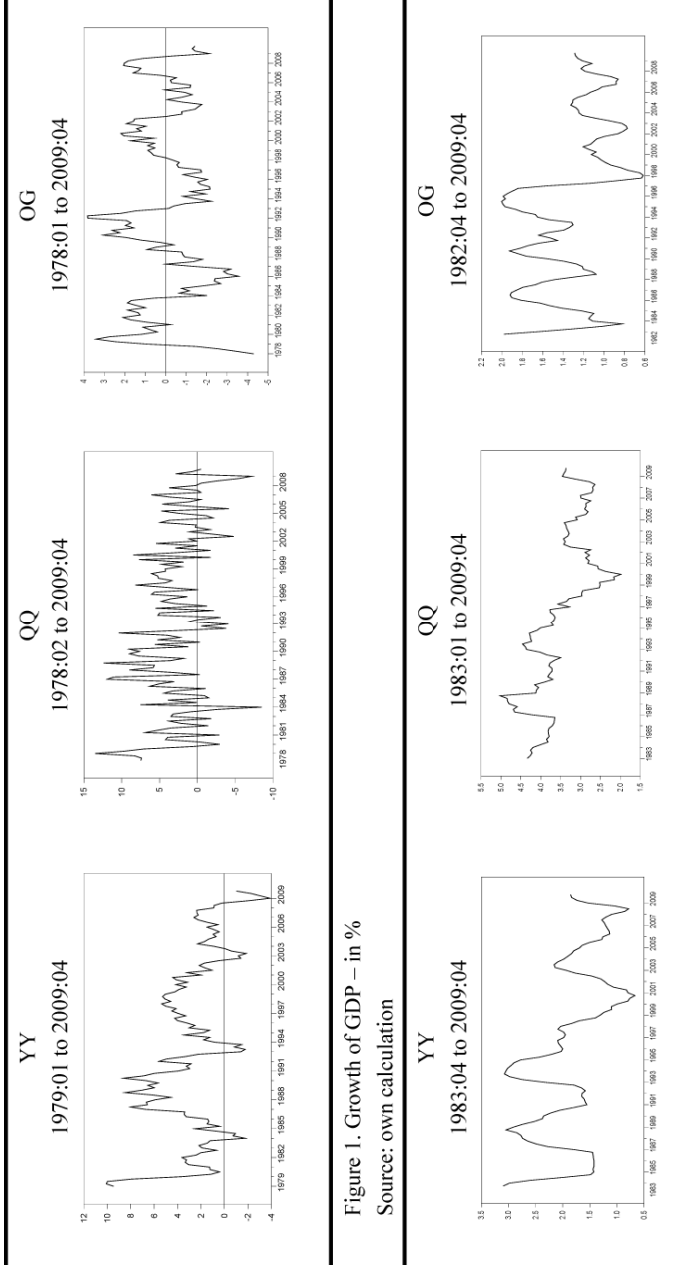


Figure 1. Growth of GDP – in %  
Source: own calculation

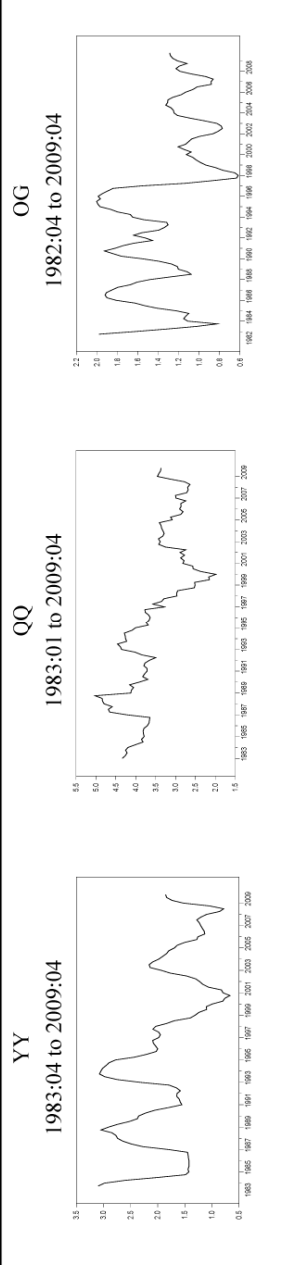


Figure 2. Standard of deviation of growth – 5-year window – in %  
Source: own calculation

Table 1  
Volatility of the GDP components - in %

	1979:01-85:04 (1)			1986:01-98:04 (2)			1999:01-09:04 (3)			1979:01-09:04 (4)			(3) - (1)		
	YY	QQ	OG	YY	QQ	OG	YY	QQ	OG	YY	QQ	OG	YY	QQ	OG
C	2.15	3.69	1.53	1.69	2.58	1.22	1.45	2.21	0.95	1.87	2.87	1.24	-0.70	-1.48	-0.57
G	0.50	0.91	0.35	0.60	0.76	0.44	0.58	0.75	0.35	0.61	0.81	0.39	0.08	-0.16	-0.00
I	4.59	6.57	2.30	2.13	3.00	1.60	1.54	2.95	1.05	2.81	4.14	1.65	-3.05	-3.62	-1.25
ΔEx	3.16	4.03	1.86	1.20	1.57	0.74	0.54	1.33	0.38	1.74	2.31	1.03	-2.62	-2.70	-1.47
X	2.59	3.30	1.75	2.08	3.05	1.46	2.49	4.43	1.73	2.49	3.70	1.64	-0.10	1.13	-0.02
M	3.37	6.12	1.95	2.85	4.39	2.12	3.55	6.54	2.48	3.30	5.67	2.25	0.18	0.42	0.53
NX	3.85	5.46	2.88	1.87	3.51	1.44	1.83	3.26	1.25	2.50	3.99	1.82	-2.02	-2.20	-1.63
GDP	3.06	4.43	1.63	2.44	3.86	1.78	2.04	3.34	1.26	2.76	4.04	1.61	-1.02	-1.09	-0.37

Notes: C means private consumption; G means public consumption; I means investment; ΔEx means inventories; X means exports; M means imports; NX means net exports; and GDP means gross domestic product.  
Source: own calculation

The decline in volatility is visible for nearly all components when we compare the period of participation in the euro area (beginning in the year 1999) with pre-EU membership (until 1985). The fall was larger for the most volatile GDP components, particularly inventories, investment, and net exports. The two exceptions are public consumption, which worsened the volatility of GDP when measured YY, and imports, which saw volatility increase. The behaviour of exports is mixed, negative for YY and OG, but positive for QQ. Public consumption reflects both the sector's relatively large weight in GDP and its intrinsic instability. The sharp fall in the volatility of exports and imports over the past three decades was not offset by increasing trade openness and the associated rise in the importance of the two variables for GDP growth. As a result, the volatility of the contribution of exports and imports increased significantly over the period, although the volatility of the contribution of net trade increased more modestly due to the strong degree of co-movement between exports and imports.

When we compare euro area membership with the pre-EU membership periods, volatility increases for both public consumption and imports. There are some possible causes for this. Membership in a monetary union means that the burden of macroeconomic stabilization, which was previously shared between the monetary/exchange policy and fiscal policy is now almost entirely reliant on fiscal policy. Since imports are a significant component of public consumption in the Portuguese economy, the stabilization function of Government contributes to making imports more volatile, too. Furthermore, the behaviour of the volatility of imports can also be explained by the decrease in the financial constraints of the Portuguese economy that occurred when the country joined the euro area. The participation in monetary union allows Portugal access to international financial markets on more favourable terms, allowing imports to respond more immediately to changes in demand (e.g. Silva, 2002; Beck et al., 2006; Bekaert et al., 2006; and Malik and Temple, 2009).

To assess the hypothesis of output composition, we employ the two following empirical techniques: (i) analysis of the effect of changes in the composition of GDP (output composition effect); and (ii) analysis of the effects of changes in the correlations between GDP components (correlation effect). It is worthwhile noting that, in the case of inventories, for which the share in GDP is close to zero, and for net exports' share in GDP, for which drift was absent (Wald test = 1.1480, with P-value of 0.2860) the actual contribution to GDP growth is used.

Figure 3 shows the changes in the composition of GDP by comparing the

observed standard deviation of GDP growth with its counterfactual standard deviation, i.e. which would have been obtained if the shares of the various GDP components had been held constant at their average value of the first five years.

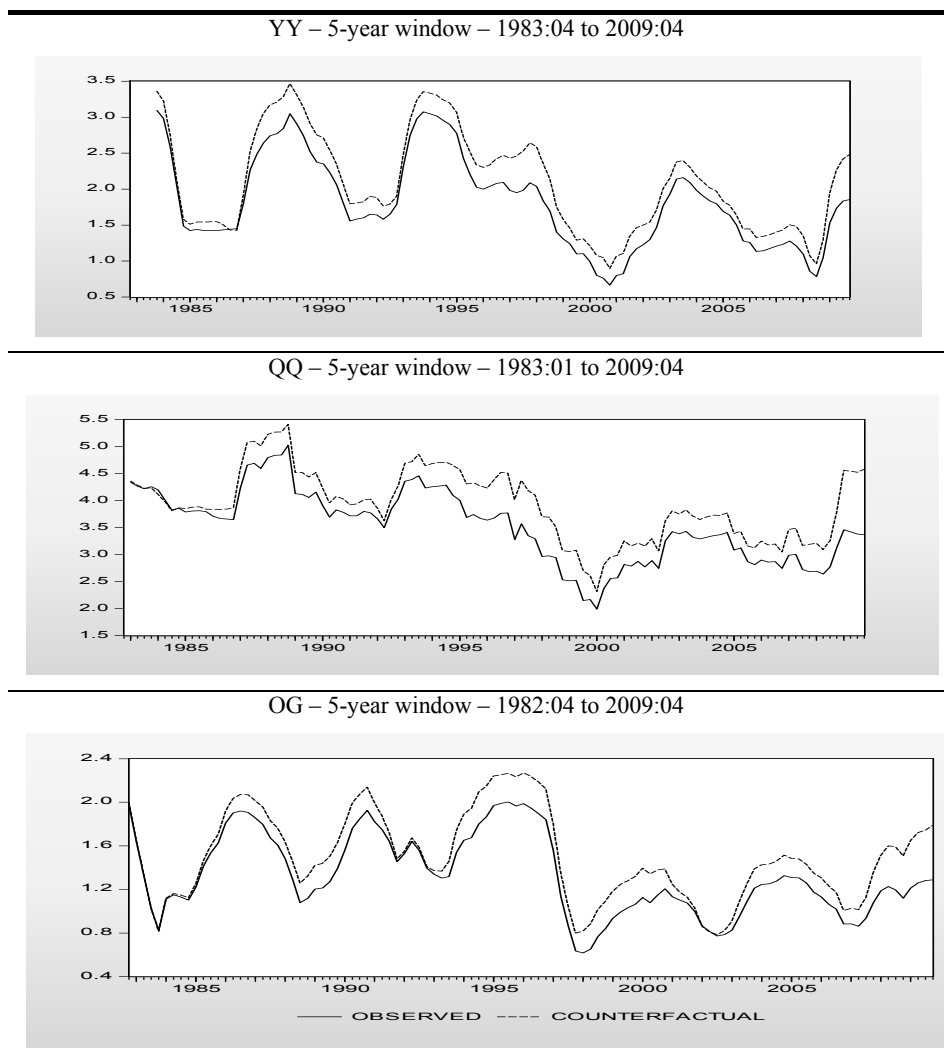


Figure 3. Effects of changes in shares of GDP components on volatility of GDP growth – in %

Source: own calculation



The two curves are close enough to suggest that their co-movements were not seriously distorted by the composition effect, which is corroborated by the low values for the Theil's variance proportion (Table 2). High correlation values support strong linearity of the volatility series (see Table 2 and Figure A1). From the regression of observed series on the counterfactual one (cf. equation 8), the Wald tests clearly reject the hypothesis that the data evolved together (see Table A2). This means that the series are statistically different. In fact, the evolution of shares of GDP components contributes to reducing the value of volatility as supported by the high values (above 0.2; see Pindyck and Rubinfeld, 1998) of Theil's bias proportion. The composition effect contributes to slowing down the volatility by 0.27%, 0.40% and 0.17%, respectively for YY, QQ and OG (see Figure A2).

Table 2  
Disparity analysis of changes in shares – in %

	YY	QQ	OG
	1983:04 to 2009:04	1983:01 to 2009:04	1982:04 to 2009:04
Correlation	0.985352	0.930678	0.960374
Mean Error	-0.269006	-0.402374	-0.174305
Mean Absolute Error	0.269599	0.404943	0.174522
Root Mean Square Error	0.296701	0.470137	0.207117
Mean Square Error	0.088031	0.221029	0.042897
Mean Percentage Error	-0.159242	-0.121748	-0.138790
Mean Absolute Percentage Error	0.159651	0.122367	0.139054
Root Mean Square Percentage Error	0.178690	0.144382	0.169751
Theil Inequality Measure	0.071659	0.062206	0.070694
Bias proportion	0.822030	0.732504	0.708255
Variance proportion	0.032548	0.000673	0.022265
Covariance proportion	0.145422	0.266823	0.269480

Source: own calculation

Figure 4 displays the changes in the correlations between GDP components on the volatility of GDP growth.

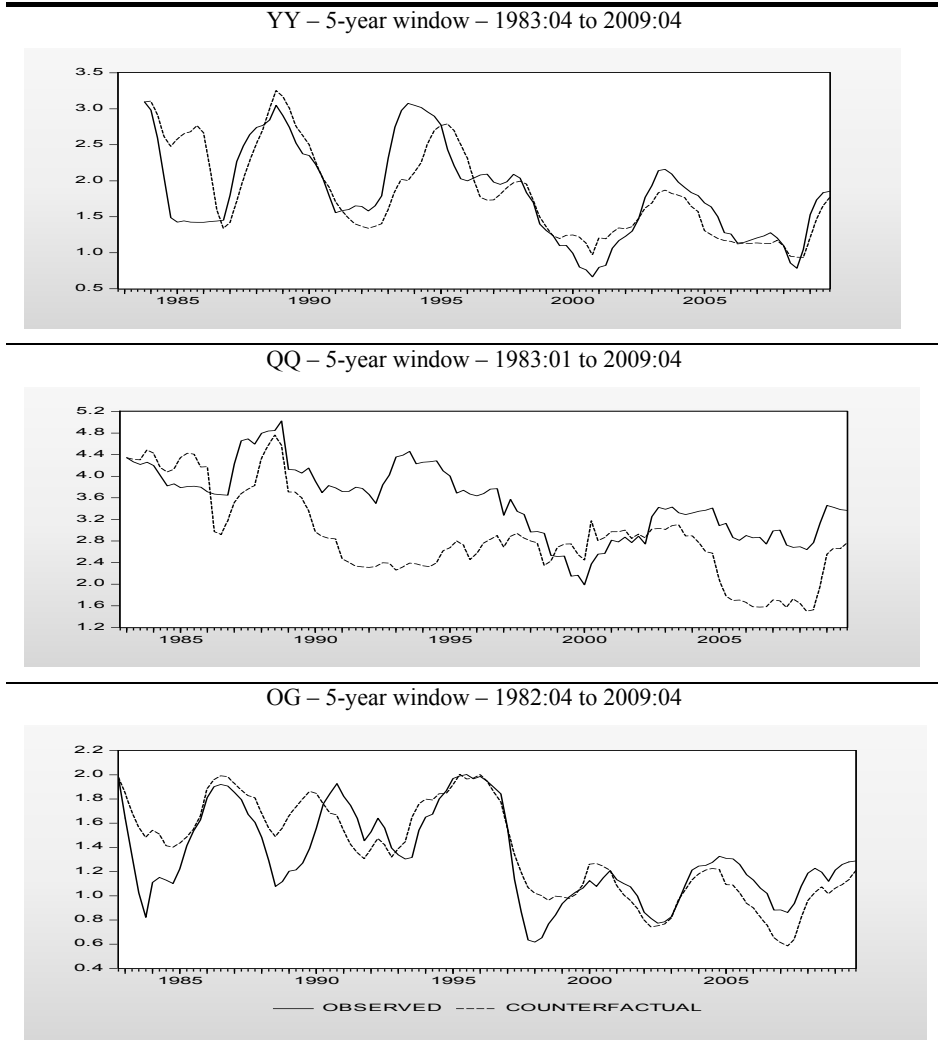


Figure 4. Effects of changes in the correlations between GDP components on volatility of GDP growth – in %

Source: own calculation

For YY and OG, the low values for the Theil's variance proportion (Table 3), suggest that the observed and counterfactual curves are similar, implying

that their co-movements were not distorted by the correlation effect. The QQ clearly reveals less graphical adhesion between series; more Theil's variance proportion and less correlation (see Table 3 and Figure A1). Like for the effect of changes in shares of GDP components, the Wald tests clearly reject the hypothesis that the data evolved together (see Table A2). Once again, the series are statistically different. The evolution of correlations between components only seems to have had an impact on QQ (Theil's bias proportion of 0.56), contributing to much more volatility, generating a positive correlation effect of 0.64% (see Figure A3). In other words, the changes in correlations between GDP components seem not to be a source of specific volatility on YY and OG, in contrast to what is observed for QQ.

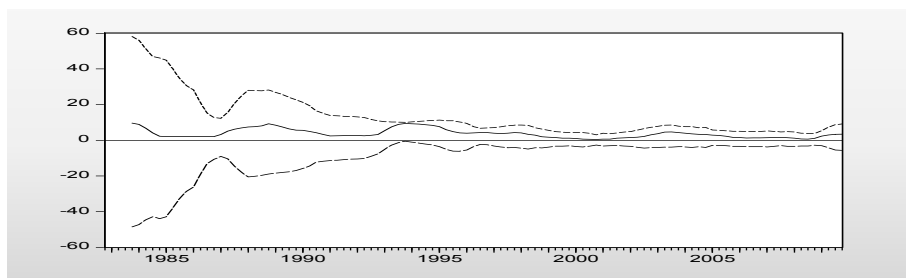
Table 3  
Disparity analysis of changes in correlations

	YY	QQ	OG
	1983:04 to 2009:04	1983:01 to 2009:04	1982:04 to 2009:04
Correlation	0.762541	0.578762	0.833462
Mean Error	-0.003129	0.636712	-0.038739
Mean Absolute Error	0.302908	0.780593	0.172915
Root Mean Square Error	0.432335	0.938676	0.225035
Mean Square Error	0.186914	0.881112	0.050641
Mean Percentage Error	-0.038382	0.174549	-0.042339
Mean Absolute Percentage Error	0.180463	0.223639	0.152579
Root Mean Square Percentage Error	0.269863	0.265068	0.217650
Theil Inequality Measure	0.111820	0.142690	0.080412
Bias proportion	0.000052	0.460103	0.029635
Variance proportion	0.001321	0.027503	0.016274
Covariance proportion	0.998626	0.512393	0.954091

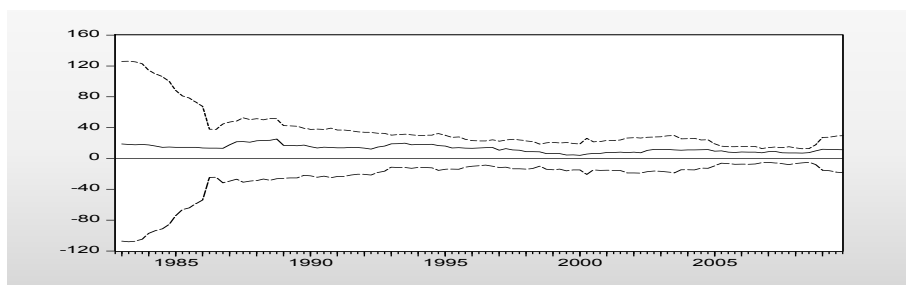
Source: own calculation

Figure 5 displays the contributions of average variance and average covariance for the "total" variance of GDP growth.

YY – 5-year window – 1983:04 to 2009:04



QQ – 5-year window – 1983:01 to 2009:04



OG – 5-year window – 1982:04 to 2009:04

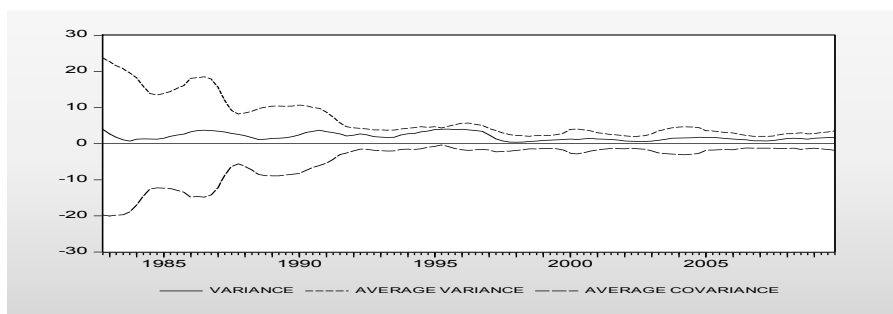


Figure 5. Variance, average variance and average covariance of GDP growth – in %

Source: own calculation

The contributions of average variance and average covariance, for the variance of GDP growth, clearly signal a structural break in the second half of the 1980s, which is more pronounced in the YY and QQ analysis. Furthermore, around 1992-3, a regime shift is perceptible, which coincides with the early stages of arrangements for the participation in the common

currency, namely by the adhesion to the Exchange Rate Mechanism of the European Monetary System.

Table 4

Correlation matrix of approaches of volatility of the GDP – 1983:04 to 2009:04

	YY	QQ	OG
YY	1.000000		
QQ	0.825238	1.000000	
OG	0.289972	0.491718	1.000000

Source: own calculation

The three alternative approaches of volatility exhibit diverse behaviours, but lead to a similar conclusion: a declining volatility. Moreover, there is a structural break near 1997-8, which coincides with the final evaluation of criteria for participation in the euro area. Actually, it seems that the expectations played a major role in the sudden decrease in volatility. Table 4 displays the correlation matrix of the three approaches to volatility, from 1983:04 to 2009:04. They have coefficients that indicate a correlation of 0.8252 between YY and QQ. The major discordance was between YY and OG, which is revealed by a correlation coefficient of 0.2900.

## 5. CONCLUDING REMARKS

This paper adds to the literature by: (i) assessing the consequences of monetary union on volatility; and (ii) extending the knowledge about growth volatility incorporating a European and small open economy. While the three alternative approaches to volatility, YY, QQ and OG, reveal divergences on the whole, they converge toward the same global conclusions. Overall, the results show a declining volatility and the strong impact of integration into the euro area on volatility behaviour.

From the analysis of the composition effect, we conclude that, on the one hand, the path of volatility is similar for observed and counterfactual series, i.e. with and without changes in the shares of the GDP components. On the other hand, the evolution of the shares contributes to slowing down the volatility. In fact, increased GDP growth stability could be partly explained by shifts in composition towards more stable GDP components. A clear downward trend is discernible in differences between observed and counterfactual series.

When we analyze the components of GDP, the major contributions to reducing volatility were inventories, investment, and net exports, while public consumption was the minor contributor. Inventories appear to play a comparatively more important role in the moderation process in the case of YY and, to a lesser extent, in the OG analysis. Consumption emerges as a more critical component in the QQ case.

As far as the correlation effect is concerned, the changes in correlations between GDP components contribute to high volatility of GDP for the QQ analysis. Furthermore, the path of observed and counterfactual series is clearly disclosed, in contrast to what happens in the YY and OG analysis, where there is no visible correlation effect.

In general, average covariance had an important role in lowering variance. This contribution was very important until the mid 1980s, when it had a relevant role limiting the high average variance. Furthermore, the decomposition of variance into average variance and average covariance sheds light on the dynamics of volatility, allowing the identification of a structural break in the second half of the 1980s, and a regime shift around 1992-3. This is the timing of the adherence to the Exchange Rate Mechanism of the European Monetary System, suggesting that the impact of monetary phenomena on volatility requires research.

We find evidence supporting the claim that both EU membership and participation in the euro area were important factors in helping to stabilize the economy. The evidence also suggests that the phase of preparation for Economic and Monetary Union was accompanied by a reduction in volatility. The decreasing path of volatility was reversed after the country became a euro area member. This somewhat unexpected result is, however, consistent with the increased structural difficulties that emerged in order to cope with the common currency.

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## APPENDIX

Table A1

Summary statistics

	Observations	Mean	Std. Error	Minimum	Maximum
Private consumption	128	19381.471375	5275.791531	11069.160349	27792.207265
Public consumption	128	5252.470912	2097.493972	2238.798946	8482.768231
Investment	128	7821.228777	1499.735704	4864.797203	10878.453387
Inventories	128	273.486831	297.859960	-309.787533	1235.352569
Exports	128	8323.495167	2793.815502	2672.808374	13809.395729
Imports	128	10899.809733	3485.017824	4462.679033	18232.138290
Net exports	128	-2576.314566	978.633627	-4654.980330	-244.369650
GDP	128	30152.343329	7890.572999	17123.089850	41324.425830

Notes: Quarterly series from 1978:01 to 2009:04, in million euros, chained volume (reference year 2006), deflator (2006 = 1).

Sources: own calculation



Table A2  
Observed and counterfactual values: Wald tests

	<b>YY</b>	<b>QQ</b>	<b>OG</b>
Wald tests	1983:04 to 2009:04	1983:01 to 2009:04	1982:04 to 2009:04
	<i>Changes in shares</i>		
Individual ( $\alpha$ )	5.164269 (0.0251)	1.917779 (0.1690)	0.005170 (0.9428)
Individual ( $\beta$ )	34.69042 (0.0000)	2.043398 (0.1558)	21.13977 (0.0000)
Jointly	335.3360 (0.0000)	148.9531 (0.0000)	166.1092 (0.0000)
	<i>Changes in correlations</i>		
Individual ( $\alpha$ )	9.835035 (0.0022)	127.8709 (0.0000)	14.83712 (0.0002)
Individual ( $\beta$ )	11.13428 (0.0012)	68.94739 (0.0000)	21.00136 (0.0000)
Jointly	5.570130 (0.0050)	109.0193 (0.0000)	12.91052 (0.0000)

Notes: Individual Wald test has as null hypothesis  $H_0 : \alpha=0$  or  $H_0 : \beta=1$ . Jointly Wald test has as null hypothesis  $H_0 : \alpha=0 \wedge \beta=1$ . Values of F-statistic. P-value in brackets.

Source: own calculation

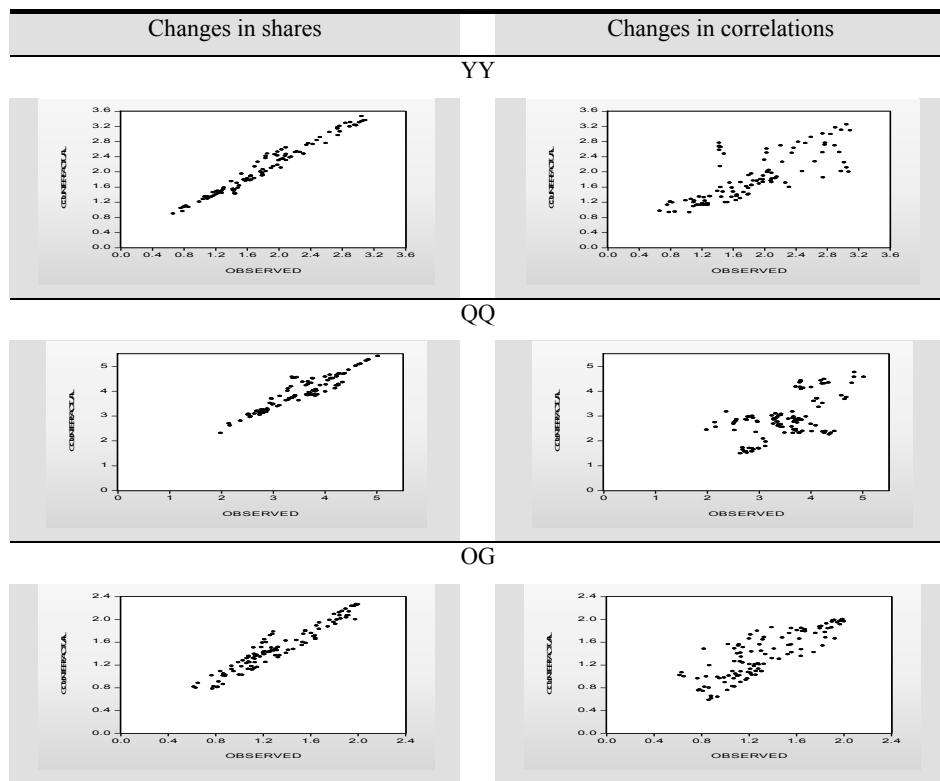


Figure A1. Scatter of counterfactual versus observed values

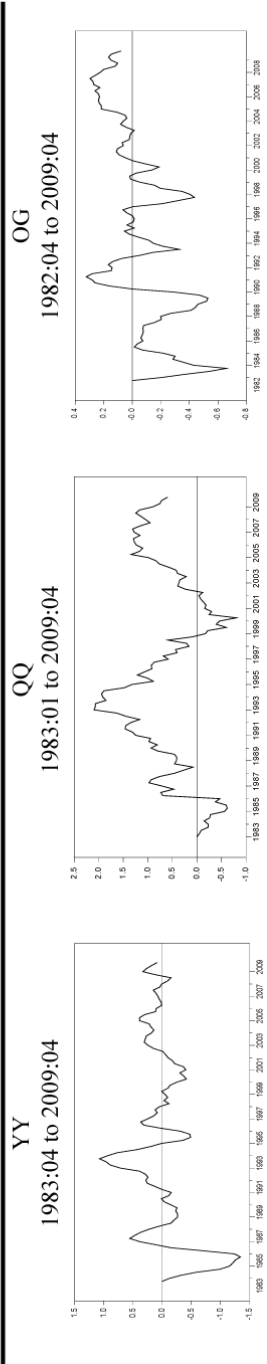
Source: authors' own calculation from the raw data from Portuguese Central Bank



Notes: Vertical axis reveals the difference between observed and counterfactual volatility series, in percentage. Sample mean of -0.2690, -0.4024 and -0.1743 for YY, QQ and OG, respectively, are significant below 1% level for t-statistic (Mean=0).

Figure A2. Effect of changes in shares of GDP components on volatility of GDP growth

Source: own calculation



Notes: Vertical axis reveals the difference between observed and counterfactual volatility series, in percentage. Sample mean of -0.0031, 0.6367 and -0.0387 for YY, QQ and OG, respectively, only significant below 1% level, for t-statistic (Mean=0), for QQ.

Figure A3. Effect of changes in the correlations between GDP components on volatility of GDP growth

Source: own calculation