The "Great Moderation" In OECD Countries: Its Deepness and Implications with Business Cycles

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This paper presents an empirical analysis of the "Great Moderation" phenomenon characterized by a decrease of volatility in GDP real growth rates, using quarterly data for the OECD member states over the period 1960-2010. This paper expands the existing literature on methodological and empirical grounds. We use a GARCH modeling approach with endogenously determined structural breaks in both the trend and volatility, which provides more accurate way to model output volatility. The objectives of this paper are threefold: (1) to assess the occurrence of "the Great Moderation" and identify the timings of volatility changes; (2) to analyse the time varying nature of volatility, in particular whether it has been subject to gradual shifts over time or one-off major shifts, as well as the degree of symmetry/asymmetry across different phases of the business cycle; (3) to analyse the dynamic pattern of (a)symmetric behaviour over the sample period. The results reveal a progressive "moderation" in all countries, characterized by regime changes in both growth rates and volatility and suggest that countries differ on the relative magnitude of the impacts of negative shocks on volatility, relatively to those of positive shocks of similar magnitude over the sample period. The disaggregated analysis over subperiods reveals an increasing pattern of these asymmetries, as well as huge differences among the countries. While this suggests a higher vulnerability to negative exogenous shocks in some OECD economies, although with different levels, some economies seem to have developed higher levels of immunity to external shocks by reaching balanced effects from positive and negative shocks.

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1. Introduction

The linkage between economies' growth rates and their volatility has long been a subject of intense debate on both theoretical and empirical grounds and no consensus has been achieved on this subject. The relevance of this issue rests on the implications of growth volatility on countries' economic development and the usefulness of getting knowledge on its behaviour as an information tool for policy design. This issue poses a particular challenge as real GDP growth involves a long run perspective over which structural changes in volatility are very likely to occur. Their occurrence has been, in fact, widely documented in the literature for several countries. Empirical evidence for the US is provided by Kim and Nelson (1999), McConnell and Perez-Quiros (2000), Blanchard and Simon (2001), and Ahmed *et al.* (2004), among others; Stock and Watson (2003), Bhar and Hamori (2003), Mills and Wang (2003), and Summers (2005) report a structural break in the volatility of the output growth rate for Japan and other G7 countries; Andraz and Norte (2012) report evidence for Portugal.. All these studies report rather dramatic reductions in GDP volatility and the coincident nature and extent of this phenomenon across many countries has earned it the label of the "Great Moderation" amongst some authors.

If the decline of GDP volatility has been widely confirmed by empirical evidence, a lack of consensus on the linkage between growth rate and volatility has emerged on theoretical grounds. On one hand, a positive relationship is suggested by the perspective that agents choose to invest in riskier and hence more volatile production technologies only if the expected rates of return (i.e., growth rates) are high enough to compensate for the associated higher risk (Black 1987), while "Schumpeterians" postulate that the economic instability generated by the process of "creative destruction" would improve the economic efficiency and thereby the long term growth. On the other hand, the idea that higher uncertainty due to higher volatility lowers output because economic agents tend to postulate their investments under instability conditions sheds light on the rationality of a negative relationship. As a result, on empirical grounds, the statistical evidence on the linkage between volatility and growth is also ambiguous. To name a few cross-sectional studies, Grier and Tullock (1989) find a positive relation while Ramey and Ramey (1995) and Martin and Rogers (2000) report a negative relation. Among time-series studies, Caporale and McKiernan (1996, 1998) find a positive relation for the UK and the US, whereas Henry and Olekalns (2002) find a negative relation for Australia and the US. Several other studies, including Speight (1999) and Grier and Perry (2000), discover no significant relation for the UK and the US, respectively.

In dealing with GDP growth volatility, some form of generalized autoregressive conditional heteroskedasticity (*GARCH*) modelling strategy has been adopted. However, most studies assume a stable *GARCH* or exponential *GARCH* (*EGARCH*) process in order to capture movements in volatility. The neglect of potential structural breaks in the output growth and/or the unconditional or conditional variances of output growth have led to high persistence in the conditional volatility or integrated *GARCH* (*IGARCH*). Particular evidence is available for Japan and the US (see Hamori 2000; Ho and Tsui 2003; and Fountas *et al.* 2004, among others). However, some papers report several problems arising when the occurrence of structural changes is neglected. Diebold (1986) first argues that structural changes may confound persistence estimation in *GARCH* models. He claims that Engle and Bollerslev's (1986) integrated *GARCH* (*IGARCH*) may result from instability of the constant term of the conditional variance (i.e., nonstationarity of the unconditional variance). Neglecting such changes can generate spuriously measured persistence with the sum of the estimated autoregressive parameters of the conditional variance heavily biased towards one. Lamoureux and Lastrapes (1990) provide confirming evidence that ignoring discrete shifts in the unconditional variance, the misspecification of the *GARCH* model can bias upward *GARCH* estimates of persistence in variance while the use of dummy variables to account for such shifts diminishes the degree of *GARCH* persistence. Alternatively, Hamilton and Susmel (1994) and Kim *et al.* (1998) suggest that the long-run variance dynamics may include regime shifts, but within a given regime, it may follow a *GARCH* process. Empirical evidence on this direction is also provided by recent studies. Mikosch and Stărică (2004) prove that the IGARCH model makes sense when non-stationary data reflect changes in the unconditional variance and Hillebrand (2005) shows that, in the presence of neglected parameter change-points, even a single deterministic change-point can cause GARCH to measure volatility persistence inappropriately. Kim and Nelson (1999), Bhar and Hamori (2003), Mills and Wang (2003), and Summers (2005) apply this approach of Markov switching heteroskedasticity with two states to examine the volatility of real GDP growth and identify structural changes.

Another relevant issue is that most, if not all, of previous studies postulate that the relation between volatility and growth is symmetric across economies' business cycles. More specifically, most empirical models implicitly assume that the sign (and size as well) of the volatility-growth relation is the same whether the economy is in contraction or expansion. However, there is no a priori reason to believe that is the case and it is conceivable that the sign of the volatility-growth relation depends on business cycle phases.

The evidence of structural changes in output growth volatility combined with high persistence in conditional volatility for several countries, in general large economies, motivates us to revisit the issue of conditional volatility in real GDP growth rates for the OECD member states, addressing the issue of potential asymmetry of the relationship between volatility and business cycles in the presence of structural breaks. Specifically, the objectives of this paper are threefold. First, we intend to assess the occurrence of "the Great Moderation" in the OECD countries and identify the timings of volatility changes. Second, is our purpose to analyse the time varying nature of volatility, in particular whether it has been subject to gradual shifts over time or one-off major shifts, as well as the degree of symmetry/asymmetry across different phases of the business cycle. Finally, is our purpose to analyse the dynamic pattern of (a)symmetric behaviour over the sample period, accounting for the different country-specific experiences.

Accordingly, the paper is organized as follows. Section 2 presents preliminary results concerning GDP growth and volatility, the relation between volatility and business cycle and the existence of structural breaks. Section 3 reports the methodological background. Section 4 reports the results on GDP volatility focusing on the asymmetric effects across the business cycle over the sample period and sub periods, accounting for the country-specific experiences. Section 5 reports the main conclusions.

2. Basic evidence of GDP volatility: Data, statistics and unit roots

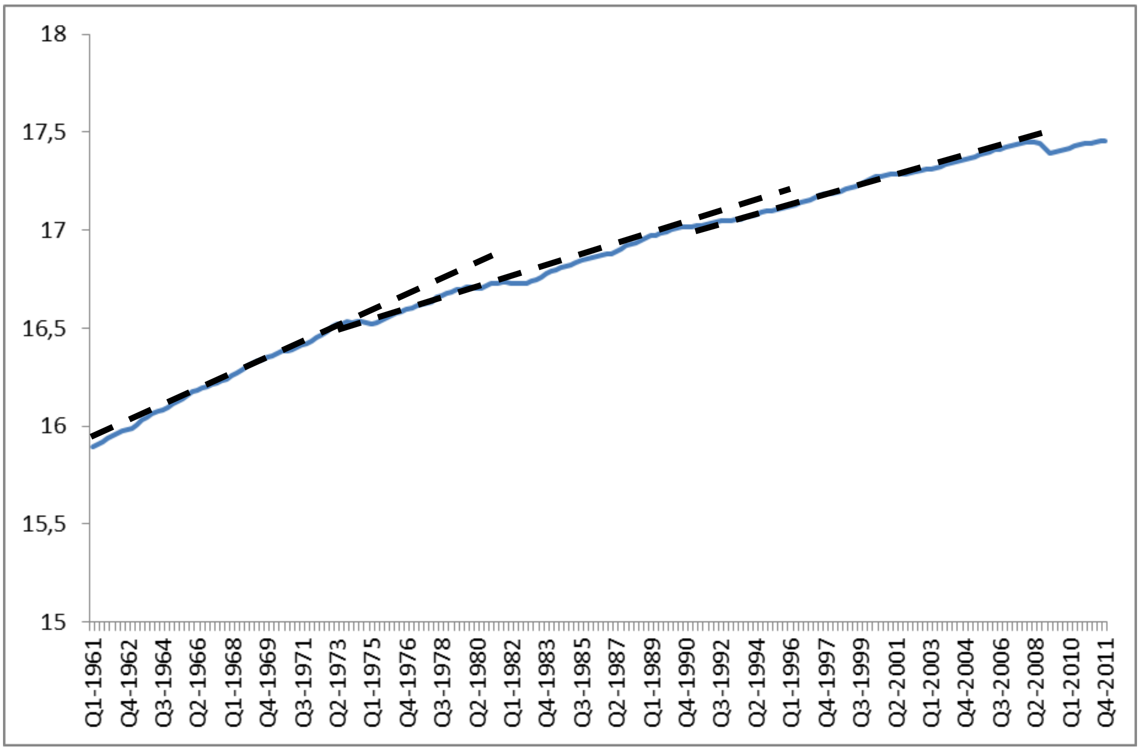
2.1 Data sources and descriptive statistics

This paper uses data on quarterly real GDP in OECD over the period 1961:1-2011:4, along with the data for the individual member state, in a total of

34 countries[1]. The data is seasonally adjusted and come from the OECD statistical database, which is available online at www.oecd.org/.

A preliminary analysis of the evolution of GDP in OECD, depicted in Figure 1, is illustrative of the decreasing trend the growth rate has shown since the 1970s. An approximate idea of the change dates can also be inferred, with the first date taking place in the 1970s, and a possible second change by the beginning of the 1990s.

Figure1. Evolution of GDP 1960:1-2011:4



Source: OECD data and authors' calculation.

This same picture emerges when analysing the annualized growth rates (y_t), as the log differences of the corresponding quarterly values, as follows

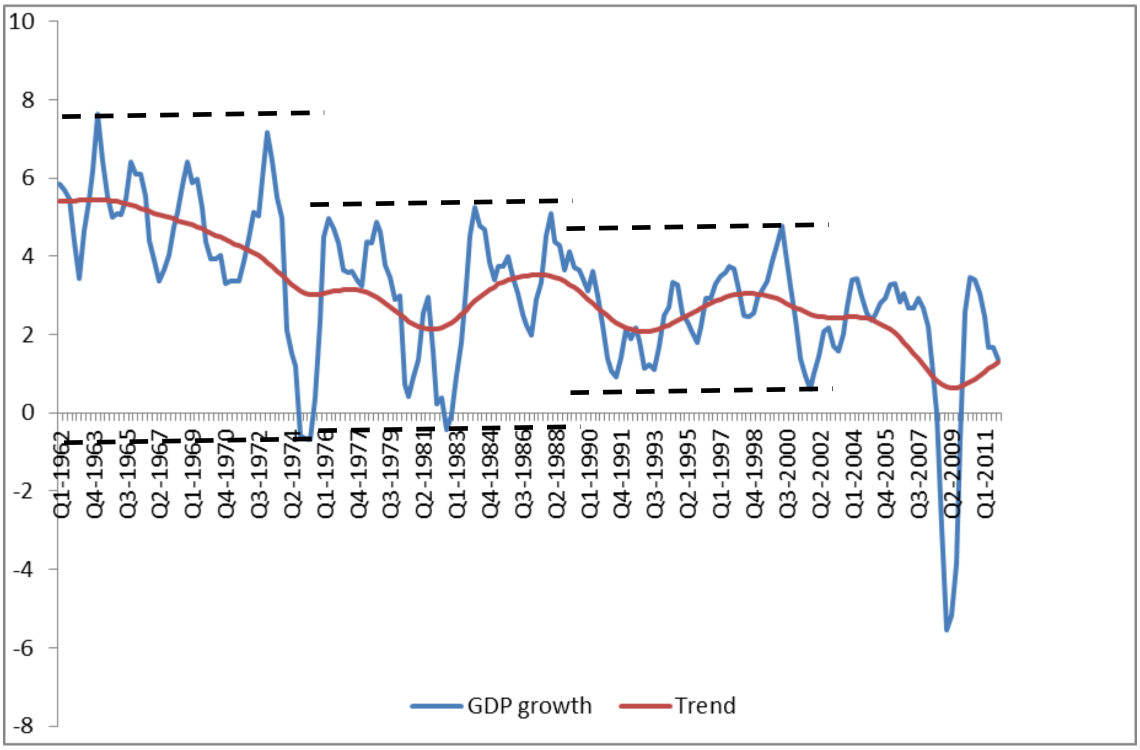
$$y_t = (\ln Y_t - \ln Y_{t-4}) \times 100, \qquad (1)$$

where Y_t is the original data series (real GDP) at quarter t, and observing its evolution, together with a simple HP filter, intended to measure the trend. GDP growth in OECD enacted a lower average growth phase since the mid-1960s, notwithstanding the occurrence of up- and downswings in the 80s and the 90s.

[1] Australia, Austria, Belgium, Canada, Chile, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Iceland, Ireland, Israel, Italy, Japan, Korea, Luxemburg, Mexico, Netherlands, New Zealand, Norway, Poland, Portugal, Slovak Republic, Slovenia, Spain, Sweden. Switzerland, Turkey, the United Kingdom and the United States of America.

Important remarks are also pointed to the quarter fluctuations, which also appear to have diminished over time, in particular over the 80s and 90s. The variation bands also indicate possible major shifts contemporaneous with the trend shifts.

Figure 2. Preliminary evidence on trend and volatility of GDP growth in OECD (1962:1-2011:4)



Source: OECD and authors' calculation.

Simple quantitative measures of the sample statistical moments are summarized in Table 1. Panel A exhibits the average growth rates and volatility measure over the sample period, in which the annual average growth achieved 3.07%, with maximum and minimum values of 7.62% in 1964:1 and -5.56% in 2009:1, while the output volatility, represented by the standard deviation, was 1.94.

The analysis of the GDP growth rate and standard deviation over shorter periods is displayed in Panel B and clearly mirrors the decline of both moments over time. The average growth rates of 5.26% per annum in the 60s and 3.60% in the 70s reduced to 2.85% in the 80s, 2.59% in the 90s and 1.83% between 2000 and 2011. The results also illustrate the significant decline in real GDP volatility since the late 1970s. After a slight increase over the 70s, the standard deviation reduced to 1.53 over the 1980s, and 0.84 over the 1990s. A slightly increase was observed again in the last decade.

Table 1. Summary statistics of real growth rates

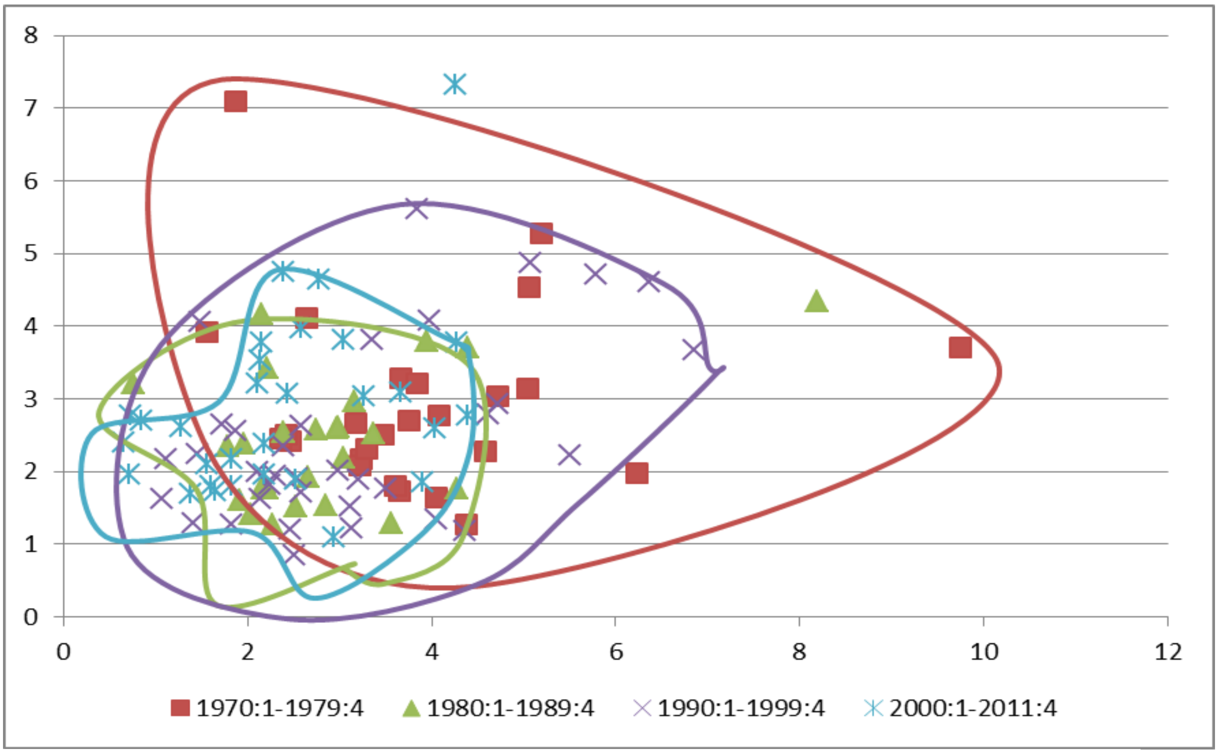
Panel A: general statistics for the sample period		
Period: 1961:1-2011:4 Mean: 3.07% Maximum: 7.62% Minimum: -5.56% St. Dev.: 1.94		
Panel B: moment statistics by decade		
Period	Sample mean (%)	Sample standard deviation
1961:1 – 1969:4	5.26	0.968
1970:1 – 1979:4	3.60	1.78
1980:1 – 1989:4	2.85	1.53
1990:1 – 1999:4	2.59	0.84
2000:1 – 2011:4	1.83	2.16

Source: OECD and authors' calculation.

Therefore, the analysis clearly illustrates the occurrence of the "Great Moderation" phenomenon in the OECD, by the end of the 70s. A more detailed analysis country by country is also illustrative of this phenomenon. By a close inspection of Figure 3, the reduction of average growth rates is common to all countries, decade after decade. It is also notorious the reduction of the dispersion.

A variety of explanations, not exclusive for any member state in particular, have been proposed for its occurrence, including a change in the structure of economies due to advances in information technology, increased resilience of economies to oil shocks, increased access to financial markets, changes in financial market regulation, improvements in the conduction of monetary policy, a reduction in the size and volatility of domestic and international shocks, among other factors. On the other hand, structural changes are very likely to occur in GDP growth time series for any number of reasons, such as economic crisis, changes in institutional arrangements, policy changes and regime shifts.

Figure 3. Growth rates and volatility among OECD member states



Source: OECD and authors' calculation.

Although many papers find no apparent break in the average growth rate of GDP for the U.S. (see McConnell and Perez-Quiros, 2000; and Blanchard and Simon, 2001, among others), others report permanent falls in average GDP growth in almost all countries. Examples include Portugal with a decline from around 5% in the 70s to just over 3% per annum in the last decade. This picture is fairly similar in timing and magnitude to the fall experienced in other countries like Canada (Voss, 2004; Debs, 2001) and Australia (Bodman, 2009). The U.S. also experienced a similar decline in volatility in the mid-80s. Therefore, this preliminary analysis clearly illustrates the suspicion that GDP growth in OECD has gone through fluctuations in trend and volatility much in the same way as in each of the member states, which should not be neglected in the analysis that follows.

2.2 Unit root tests

In this subsection we analyse whether or not unit roots exist in the real growth rate by applying the Augmented Dickey-Fuller (Dickey and Fuller, 1979, 1981) test (ADF test), the DF-GLS test and the Phillips and Perron (1988) test (PP test), as stationary is required to obtain reliable parameters estimates and statistical inference. The results are reported in Table 2 and correspond to the estimation of the auxiliary regression with a constant term and with a constant and a time trend. The ADF test uses a fourth period of augmentation term and the PP test uses the fifth degree of Bartlett Kernal's lag truncation. All the results show that the null hypothesis of the existence of a unit root is rejected[2].

Table 2. Unit root tests

AFD		DF GLS (ERS)		PP	
Constant	Constant and trend	Constant	Constant and trend	Constant	Constant and trend
-5.810* [0.000]	-6.589* [0.000]	-3.828*	-4.721*	-3.160* [0.025]	-3.849* [0.030]

Note: * indicates statistical significant values; p-values in brackets; the critical values of the DF-GLS test considering a constant term in the regression are -2.585 (1%), -1.942 (5%) and -1.615 (10%). Considering a constant and a time trend: -3.562(1%), -3.015 (5%) and -2.725 (10%).

3. Methodological framework

3.1 On the existence and nature of structural changes

The issue of structural changes is of considerable importance in the analysis of macroeconomic time series as the consequences of not considering their existence in the specification of an econometric model are dramatic for statistical inference and the estimates credibility. In fact, results may be biased towards the erroneous non-rejection of the non-stationarity hypothesis (Perron, 1989, 1997; Leybourne and Newbold, 2003) and to the erroneous conclusion that the series under analysis has a stochastic trend. This, in turn, implies that any shock – whether demand, supply, or policy-induced – to the variable will have effects on the variable into the very long run. Whilst this drawback does not seem to be relevant in our analysis since the stability of growth rates is guaranteed, major implications on parameters estimates may subsist.

An associated problem is that of testing the null hypothesis of structural stability against the alternative of a one or two-time structural breaks, as the previous analysis suggested the possible existence of two structural breaks in

[2] The analysis was also performed by using White´s heteroscedasticity-consistent standard errors. The conclusion on the rejection of a unit root remains unchanged.

the GDP growth rates in the 80s and the 90s. Conventional tests assume that the potential break date is known *a priori* and they are then constructed by adding dummy variables representing different intercepts and slopes, thereby extending the standard Dickey-Fuller procedure (Perron 1989). However, this standard approach has been criticized (see, for example Christiano 1992), as it invalidates the distribution theory underlying conventional testing. In response, a number of studies have developed different methodologies to determine breaks endogenously, showing thereby that bias in the usual unit root tests can be reduced (Zivot and Andrews 1992; Perron 1997; Lumsdaine and Papell 1997; and Bai and Perron 2003).

Perron and Vogelsang (1992) and Perron (1997) have proposed a class of test statistics which allows for two different forms of a structural break, namely, the Additive Outlier (AO) model, which is more relevant for a series exhibiting a sudden change in the mean (the crash model), and the Innovational Outlier (IO) model, which captures changes in a more gradual manner through time. However, those tests capture only one (the most significant) structural break in each variable. Considering only one endogenous break is not sufficient and it leads to a loss of information, particularly in our case when it is likely to have occurred more than one break. In this same issue, Ben-David *et al*. (2003, p. 304) argued, that "just as failure to allow for one break can cause non-rejection of the unit root null by the Augmented Dickey-Fuller test, failure to allow for two breaks, if they exist, can cause non-rejection of the unit root null by the tests which only incorporate one break".

In face of such limitations, and given the period under analysis, over which several economic and political arrangements have taken place, we opt to use the Lumsdaine and Papell (1997) test (LP test thereafter), which is able to capture two structural breaks. The test is an extension of the Zivot and Andrews (1992) test (model C), and it uses a modified version of the ADF test which is augmented by two endogenous breaks as follows

$$\Delta y_t = \mu + \beta t + \theta DU1_t + \gamma DT1_t + \varpi DU2_t + \psi DT2_t + \alpha y_{t-1} + \sum_{i\_1}^{k} c_i \Delta y_{t-i} + \varepsilon_t \qquad (2)$$

where $DU1_t = 1$ if $t > TB1$ and otherwise zero; $DU2_t = 1$ if $t > TB2$ and otherwise zero; $DT1_t = t - TB1$ if $t > TB1$ and otherwise zero; and $DT2_t = t - TB2$ if $t > TB2$ and otherwise zero.

Two structural breaks are allowed in both the time trend and the intercept and this model is referred to as the CC model (similar to the Zivot and Andrews C model, which captures a single break point) in the literature. The two indicator dummy variables ($DU1_t$ and $DU2_t$) capture structural changes in the intercept at time $TB1$ and $TB2$ respectively. The other two dummy variables, i.e., $DT1_t$ and $DT2_t$ capture shifts in the trend variable at time $TB1$ and $TB2$ respectively. The optimal lag length (k) is determined based on the general to specific approach /the $t-$test) suggested by Ng and Perron (1995). The “trimming region”, in which we have searched for $TB1$ and $TB2$, cover the $0.05T - 0.95T$ period. We have selected the break points ($TB1$ and $TB2$) based on the minimum value of the t statistic for α. Using annual time series data, Lumsdaine and Papell (1997) and Ben_David *et al*. (2003) have assumed the lag length (k) to vary up to $K_{\max} = 8$. The null hypothesis is that α=0 in Equation (2), which implies that there is a unit root in y_t. The alternative hypothesis is that α<0, which implies that y_t is breakpoint stationary.

3.2 On GDP volatility modelling

The *ARCH* models are design to model and forecast the conditional variance. In each case the variance of the dependent variable is specified to depend upon past values of the dependent variable using some formula. A general *ARMA(r,s)-GARCH(p,q)-M* process is specified as follows,

$$\Phi(L)y_t = \mu + \Theta(L)u_t + \delta h_t \tag{3}$$

$$B(L)h_t = \varpi + A(L)u_t^2 \tag{4}$$

where,

$$\Phi(L) = 1 - \sum_{j=1}^{r} \phi_j L^j; \qquad \Theta(L) = -\sum_{j=1}^{s} \theta_j L^j; \qquad B(L) = 1 - \sum_{i=1}^{p} \alpha_i L^i; \qquad A(L) = \sum_{i=1}^{q} \beta_i L^i;$$

Let $\{u_t\}$ be a real-valued time series stochastic process generated by $u_t = e_t h_t^{1/2}$, where $\{e_t\}$ is a sequence of independent, identically distributed (*i.i.d.*) random variables with zero mean and unitary variance; h_t is positive with probability one and is a measurable function of $\sum_{t-1}$ which in turn is the sigma-algebra generated by $\{u_{t-1}, u_{t-2},...\}$. That is, h_t is the conditional variance of the errors $\{u_t\}$, $\left(u_t \middle| \sum_{t-1}\right) \sim (0, h_t)$. This turns the current variance depending upon three factors: a constant, past news about volatility, which is taken to be the squared residual from the past (the *ARCH* terms) and past forecast variance (the *GARCH* terms). For the remaining, *r* and *s* correspond to the order of the *ARMA* process for the conditional mean; *p* and *q* correspond to the order of the *GARCH* process for the conditional variance.

The potential dependency of the nature of the volatility-growth relation on the business cycle phase requires the use of methods that account for this asymmetry. One of those methods of describing this asymmetry in variance is the *T-GARCH* model, which was introduced independently by Zakoian (1994) and Glosten *et al*. (1994). The model for the variance is given by,

$$B(L)h_t = \varpi + A(L)u_t^2 + C(L)u_t^2 \qquad (5)$$

where $C(L) = \sum_{i=1}^{q} \beta_{i+1} I_{t-1} L^i$ and $I_{t-i} = 1$ for $u_t < 0$ and zero otherwise.

This *T-GARCH* specification allows the impacts of lagged squared residuals to have different effects on volatility depending on their sign. While good news, given by $u_{t-i} > 0$ have an impact of α_i, bad news, expressed by $u_{t-i} < 0$ have an impact of $\alpha_i + \sum_{i=1}^{q} \beta_{i+1}$. Significant values for the leverage effect coefficients suggest asymmetries, with negative (positive) shocks having a greater impact upon volatility whether $\sum_{i=1}^{q} \beta_{i+1} > 0 \left(\sum_{i=1}^{q} \beta_{i+1} < 0 \right)$.

Another approach to investigate whether fluctuations in GDP volatility are associated with GDP growth is to estimate an exponential *GARCH (EGARCH)* in which the variance formulation captures asymmetric responses in the conditional variance (Nelson, 1991). Generalizing, the formulation for the conditional variance for an *EGARCH(p,q)* process is as follows:

$$B(L)\ln(h_t) = \varpi + C(L)z_t$$

$$z_{t-i} = \beta_1 \frac{u_{t-i}}{\sqrt{h_{t-i}}} + \beta_2 \left[\frac{|u_{t-i}|}{\sqrt{h_{t-i}}} - E\left| \frac{u_{t-i}}{\sqrt{h_{t-i}}} \right| \right], \qquad (6)$$

where $C(L)=\sum_{i=1}^{q} c_i L^i$ and $B(L)=\prod_{i=1}^{p}(1-\alpha_i L)$, with $c_i = 1$.

4. Volatility and growth cycles: asymmetries and time varying patterns

This section provides the model specification that best describes the conditional mean and conditional variance of GDP growth rates, accounting for the potential occurrence of structural breaks in both the mean and variance, with the ultimate objective of analysing the dependence upon the business cycle and the time varying nature of such relationship. This is the motivation of this section.

4.1 Dating the structural changes on GDP growth moments

The results of the LP test are reported in Table 3, where the possible existence of two structural breaks can be assessed. Either or both the conditional mean and the conditional variance are allowed to break at two possible different dates. The trimming region, where structural changes have been searched for, covers the period from 1966:1 to 2006:4. The null hypothesis of a unit root in GDP growth rate is rejected for the conditional mean in favour of the two breaks alternative in 1983:1 and 1995:4. The estimated coefficients for θ and ω are significant, indicating that structural changes have impacted on the intercept. To test for the instability of the volatility (the conditional variance), the structural breaks were included in the growth rate series and the non-constant mean was removed. The null hypothesis of a unit root is again rejected in the case of the conditional variance, in favour of the existence of two structural breaks in 1978:2 and 1983:2. Once again, the coefficients of the dummy variables report statistically significant impacts of structural changes on both the intercept and trend.

Table 3. Lumsdaine and Papell test for structural changes

Real GDP growth	$TB1$ $TB2$	μ	β	θ	Γ	ω	ψ	α	K
Conditional mean	1983:1 1995:4	1.466* (4.95)	-0.014* (-3.57)	0.665* (3.13)	0.001 (0.23)	0.528* (2.45)	-0.007 (-0.10)	-0.257* (-4.87)	8
Conditional standard deviation (breaks in the mean)	1978:2 1983:2	0.066 (0.41)	-0.002 (-0.44)	1.017* (2.93)	-0.099* (-3.96)	1.099* (3.87)	0.100* (4.03)	-0.386* (-5.63)	8

Source: Authors' calculation.

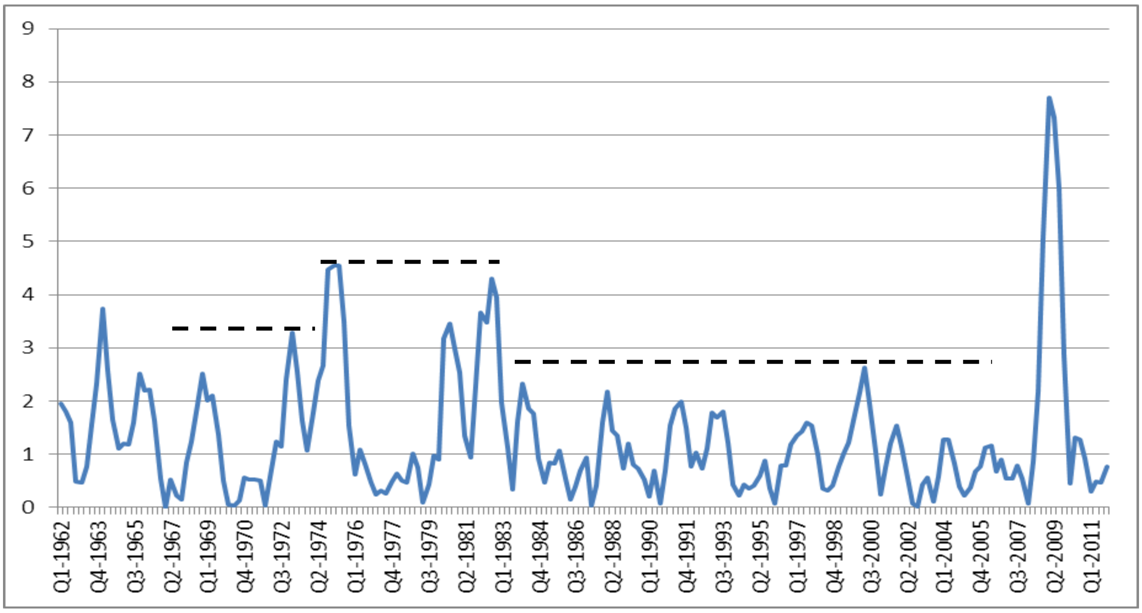
Note: t-values in square brackets; * indicates statistical significance at the 5% level.

Equation specification: $\Delta y_t = \mu + \beta t + \theta DU1_t + \gamma DT1_t + \omega DU2_t + \psi DT2_t + \alpha y_{t-1} + \sum_{i=1}^{K} c_i \Delta y_{t-i} + \varepsilon_t$

4.2 Assessing the structural changes nature

Prior to volatility modelling, an assessment of the structural changes nature is required, in particular, whether they have been gradual shifts over time or one-off major shifts type. To further investigate on this issue, we analyse the volatility pattern across the sample period, generated by the absolute value of the demeaned annual growth rate, which is illustrated in Figure 4. By visual inspection is perceptible breaks occurrence in the beginning of the 80s and the middle 80s. The changes appear to be of one-off major shifts type, instead of being gradual over time.

Figure 4. GDP growth rate volatility 1962:1-2011:4



Source: OECD and authors' calculation.

As a more formal test is required, we opt to use the Nyblom's L test (Nyblom 1989), which assumes parameter's constancy as the null (against instability of general form at some unknown date thereby representing an improvement over other tests like the Chow test or the CUSUM test). The results are reported in Table 4. We first estimate a p-order autoregressive model, *AR(p)*, of the demeaned GDP growth series, given by (8), and looked for instability in each parameter.

Model 1: $$\Phi(L)y_t = \mu + u_t \tag{8}$$

where $\Phi(L) = 1 - \sum_{i=1}^{p} \phi_i L^i$.

The values of the AIC and SBC criteria are minimized for a 4th order autoregressive model[3]. The values of the test statistic for a break in each parameter are displayed in the first column and suggest that although parameter´s stability cannot be rejected, the stability of residual variance is rejected at a level of significance lower than 5%.

In face of the previous results suggesting the non-constancy of the variance, the test is then applied to the error variance, which is estimated as the squared residuals from the *AR(5)* model, expressed by

[3] The results are not provided here but are available upon request.

Model 2: $$\sigma_t^{\ 2} = \mu + \Theta(L)u_t^2 + v_t \qquad (9)$$

where , $\Theta(L) = 1 - \sum_{i=1}^{4} \phi_i L^i$

The results of the Nyblom’s test are reported in the second column and they confirm again the variance instability. Finally, regime shift dummies, corresponding to breaks detected in 1978:2 and 1983:2, are included in the model, as follows:

Model 3: $$\sigma_t^{\ 2} = \beta_0 + \Theta(L)u_t^2 + \rho_1 DT1 + \rho_2 DT2 + \vartheta_t \qquad (10)$$

Table 4. Nyblom´s test statistic for parameter stability in GDP growth and conditional error variance of GDP growth

Parameters	Model 1	Model 2	Model 3	5% critical values
μ	0.0308	0.0219	0.0491	0.47
ϕ_1	0.1486	0.3515	0.2531	0.47
ϕ_2	0.0918	0.0804	0.1315	0.47
ϕ_3	0.2099	0.1057	0.1593	0.47
ϕ_4	0.0451	0.0864	0.0639	0.47
ρ_1			-0.5893	0.47
ρ_2			-0.7381	0.47
σ^2	0.5868	0.6757	0.0537	0.47
Joint Lc (5% critical values)	1.5857 (1,90)	1.3697 (1,68)	1.5453 (1,68)	

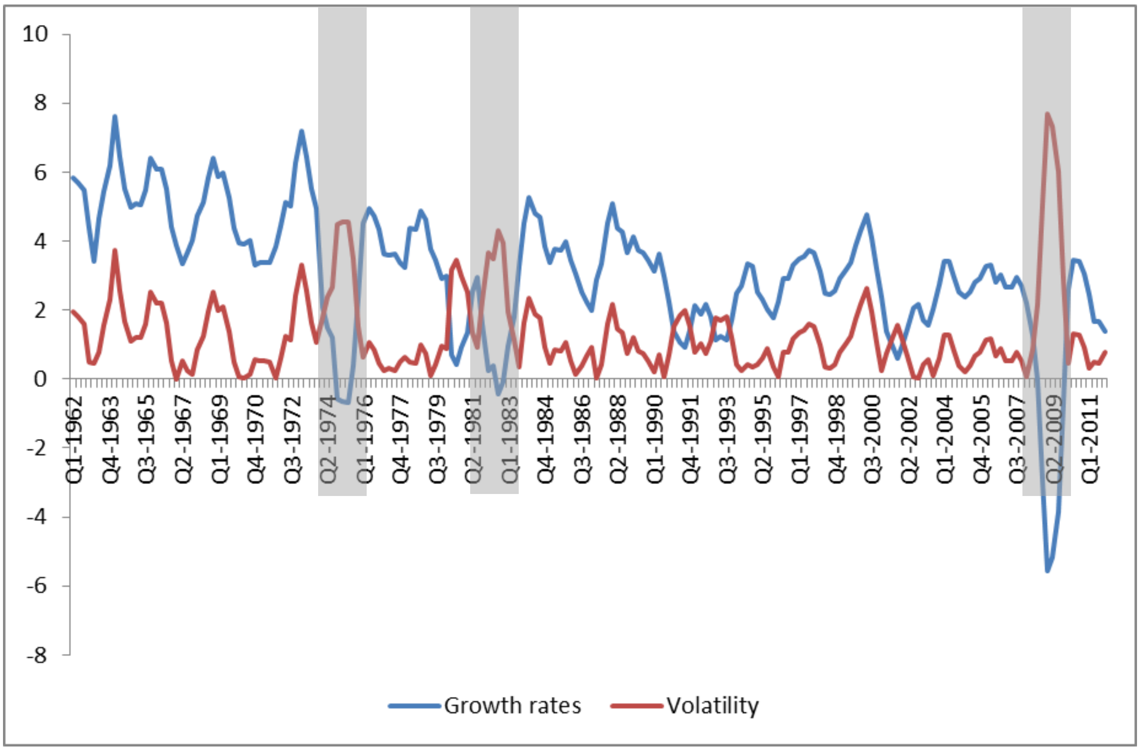
Source: Authors’ calculation.
Notes: * and ** Indicates statistical significance at the 5% and 10% levels, respectively.
The Nyblom´s test assumes coefficients stability as the null. Results are robust to other model specifications.

The results, in the third column, report no evidence of instability in any parameter, which is suggestive of significant shifts to lower volatility regimes being captured by binary dummy variables. The negative values of the ρ parameters suggest a shift from high variance to low variance regimes.

4.3 GARCH modelling: features of GDP growth volatility over 1962:1 to 2011:4

The demeaned real GDP growth, e.g., real filtered GDP growth obtained by removing the non-constant mean provides a measure GDP volatility once the mean regime shifts are taken into account. Volatility is represented in Figure 5, together with GDP annual growth rates and two remarks are in order. First the trend change of volatility over the sample and, second, the apparent negative association between volatility and GDP growth rates arise the suspicion of different behaviour over the business cycle.

Figure 5. GDP volatility and the business cycle



Note: the shaded bars indicate recessions. Volatility is computed using the absolute value of the demeaned annual growth rate.
Source: OECD and authors' calculations.

In all models that follow, the dependent variable is the demeaned real GDP growth, that is, real GDP growth filtered to remove the non-constant mean, accounting for the estimated regime shifts in 1983:1 and 1995:4. Following standard Box-Jenkins ARIMA modelling procedure, and considering the model selection criteria, GDP growth is best modelled as an ARMA(2,4) (results of the model selection are not provided here, but are available upon request). The results on coefficients' estimation are reported in Table 5 along with the residuals diagnostic tests. Almost all coefficients estimates are statistically significant at the 5% level and there is no evidence of residual autocorrelation. The LM test for residuals autocorrelation provides evidence towards the non rejection of the null hypothesis whilst the Ljung-Box tests indicate that significant persistence is still observed in the squared residuals. In order to check for heteroskedasticity behaviour in residuals, we employ the LM tests for ARCH for 20 lags. The results, considering 1 and 5 lags are illustrative and show that the assumption of constant error variance is not appropriate when modelling GDP growth rate, as there is significant uncaptured structure in the second moment. Further analysis with the BDS tests indicates the existence of nonlinearities in the residuals.

Table 5. ARMA model of Filtered GDP growth: 1962-2011
(regime shifts in the mean in 1983:1 and 1995:4)

$$y_t = -0.21643^{**} + 1.53593^{**} y_{t-1} - 0.56527^{**} y_{t-2} - 0.11244^{**} \varepsilon_{t-1} + 0.02436 \ \varepsilon_{t-2}$$
$$(0.098) \quad (0.063) \quad (0.062) \quad (0.038) \quad (0.037)$$
$$-0.023562 \varepsilon_{t-3} - 0.86409^{**} \varepsilon_{t-4}$$
$$(0.032) \quad (0.055)$$

$R^2 = 0.914$	
$LM - test(2) = 0.1218 \quad [0.8853]$	$LM - test(5) = 1.0392 \quad [0.3962]$
$\text{Jarque - Bera} = 57.381 \quad [0.000]$	
$Q^2(7) = 9.6414 \quad [0.002]$	$Q^2(10) = 11.075 \quad [0.026]$
$LM - ARCH(1) = 6.8315 \quad [0.010]$	$LM - ARCH(5) = 1.8874 \quad [0.098]$
$BDS(3,1) = 0.056 \quad [0.000]$	$BDS(5,1.5) = 0.071 \quad [0.000]$

Source: Authors' calculation.
Note: standard errors in square brackets and p-values in brackets;

To address these inadequacies and allow for time varying conditional variances, a *GARCH*(*p,q*) modelling procedure of the squared residuals was implemented. The corresponding results are reported in Table 6 (column 1) along with the residuals diagnostic tests.

The best (lowest AIC and SBC best residuals diagnostics) specification includes a highly significant deterministic shift dummy in the variance term of a *ARMA(2,4)_GARCH(1,1)* specification. The coefficients' estimates in the conditional mean specification are still significant at the 5% or, at least, the 10% levels. Regarding the conditional variance specification, the process stability is guaranteed and the long-run volatility is 0.31%. The coefficient of lagged conditional variance term in the conditional variance equation is also highly statistically significant, although the coefficient of the lagged square residual is not. Nevertheless, their sum is well below one, which implies that shocks to the conditional variance are not very persistent. The dummy's coefficient is negative, confirming the shift from a high to a lower volatility regime.

Table 6. Time varying volatility and asymmetric responses of volatility: 1962-2011 (regime shifts in the mean in 1983:1 and 1995:4)

Parameters	ARMA(2,4)-GARCH(1,1)	ARMA(2,4)-TGARCH(1,1)	ARMA(2,4)-EGARCH(1,1)
μ	0.06975* (0.225)	0.15910 (0.255)	0.13357 (0.238)
ϕ_1	1.44701** (0.078)	-0.29087** (0.076)	-0.22766 (0.183)
ϕ_2	-0.48240** (0.076)	0.45119** (0.069)	0.41446** (0.089)
θ_1	-0.05364 (0.063)	1.61125** (0.008)	1.56496** (0.194)
θ_2	0.03382 (0.059)	1.49397** (0.018)	1.45621** (0.193)
θ_3	-0.03857 (0.055)	1.44664** (0.026)	1.41038** (0.178)
θ_4	-0.08437** (0.053)	0.57199** (0.022)	0.52684** (0.177)
ϖ	0.19507** (0.075)	0.29589** (0.111)	-0.59364** (0.208)
α_1	0.01421 (0.188)	0.09522 (0.261)	0.63695** (0.109)
β_1	0.38667** (0.0983)	0.04827 (0.127)	-0.20713** (0.124)
β_2		0.38054* (0.203)	0.32756* (0.179)
ψ_1	-0.50972** (0.225)		
ψ_2	-0.07787 (0.059)	-0.18701** (0.083)	-0.31976** (0.145)
R^2	0.910	0.908	0.907
J-B	2.351 [0.309]	1.7008 [0.412]	2.3627 [0.310]
LM ARCH (1)	0.0122 [0.912]	0.044 [0.834]	0.1441 [0.705]
LM ARCH (5)	0.0971 [0.993]	0.0802 [0.995]	0.2219 [0.953]

Source: Authors' calculation.

Note: Bollerslev-Wooldridge robust standard errors in square brackets; p-values in brackets; * indicates statistical significance at 10% level; ** indicates statistical significance at 5% level or less.

Model ARMA(2,4): $\left[1-\sum_{j=1}^{2}\phi_j L^j\right]y_t = \mu + \sum_{j=1}^{4}\theta_j L^j u_t$

Model ARMA(2,4)-GARCH(1,1):

$$[1-\alpha_1 L]h_t = \omega + \beta_1 L u_t^2 + \psi_1 DT1_t + \psi_2 DT2_t$$

Model ARMA(2,4)-TGARCH(1,1) $[1-\alpha_1 L]h_t = \omega + \beta_1 L u_t^2 + \beta_2 I_{t-1} L u_t^2 + \psi_2 DT2_t$

Model ARMA(2,4)-TGARCH(1,1): $(1-\alpha_1 L)Ln(h_t) = \omega + z_{t-1} + \psi_2 DT2_t$

DT1 are dummy variables: DT1=0 before 1978:1 and after 1983:2; DT2=0 before 1983:2.

4.4 Volatility asymmetries: the cyclical features of volatility and the business cycle dependence

After having identified the main issues on volatility major changes, e.g. their timing and nature, and having estimated the model that best describes its behaviour, the analysis of the volatility behaviour over business cycles different phases is of empirical relevance for the design of the policy-decision process.

By plotting together the volatility and the GDP growth, as shown in Figure 5, it is possible to notice some interesting remarks. First, periods of positive growth seem to be characterized by a positive relationship between growth rates and volatility. Because expansions last longer than contractions, the volatility average values lie closer to the values it reaches during expansions. Consequently, deviations from output growth average are larger during periods of lower growth. This cyclical pattern seems to suggest the existence of potential asymmetries associated to the business cycle. Second, we observe periods of increased volatility, in particular, around 1975, 1982 and 2009. As these years coincide with recessions of the product in the OECD, it seems that the asymmetry of the business cycle may account for part of the increase in measured volatility during recessions.

To further analyse on this issue, and given the asymmetry observed in different phases of the business cycle, we estimate a *TGARCH* and *EGARCH* models and the results are reported in columns 2 and 3 of Table 6, along with the residuals diagnostic tests. Both models report a statistical significant leverage effects. The leverage effect estimated in the *TGARCH* is positive, which postulates that while the impact of good news on variance is 0.048, the impact of bad news is more than 8 times higher, 0.429. Considering the *EGARCH* model estimates, the magnitude effect is again positive, corresponding to 0.328, while the leverage effect is negative, corresponding to -0.207. Once again, the asymmetric effects are confirmed with the impact of negative shocks being more than four times the impact of positive shocks of identical magnitude. Therefore, the statistical significance of the leverage effects, along with their signs suggests that negative shocks to GDP growth cause higher volatility than positive shocks, thereby increasing the degree of uncertainty during recessions, and causing asymmetries of the corresponding news impact curves.

4.5 The time varying asymmetric nature of volatility

Having detected a volatility change in GDP growth rates, an analysis is conducted to further investigate whether the asymmetric effects exhibit a persistent pattern over time, or the volatility decline is associated with a change of the business cycle asymmetric effects on volatility. The estimated results for the periods before and after the regime change in volatility, centred in 1983:1, considering parsimonious specifications (lowest AIC and SIC) are reported in Table 7.

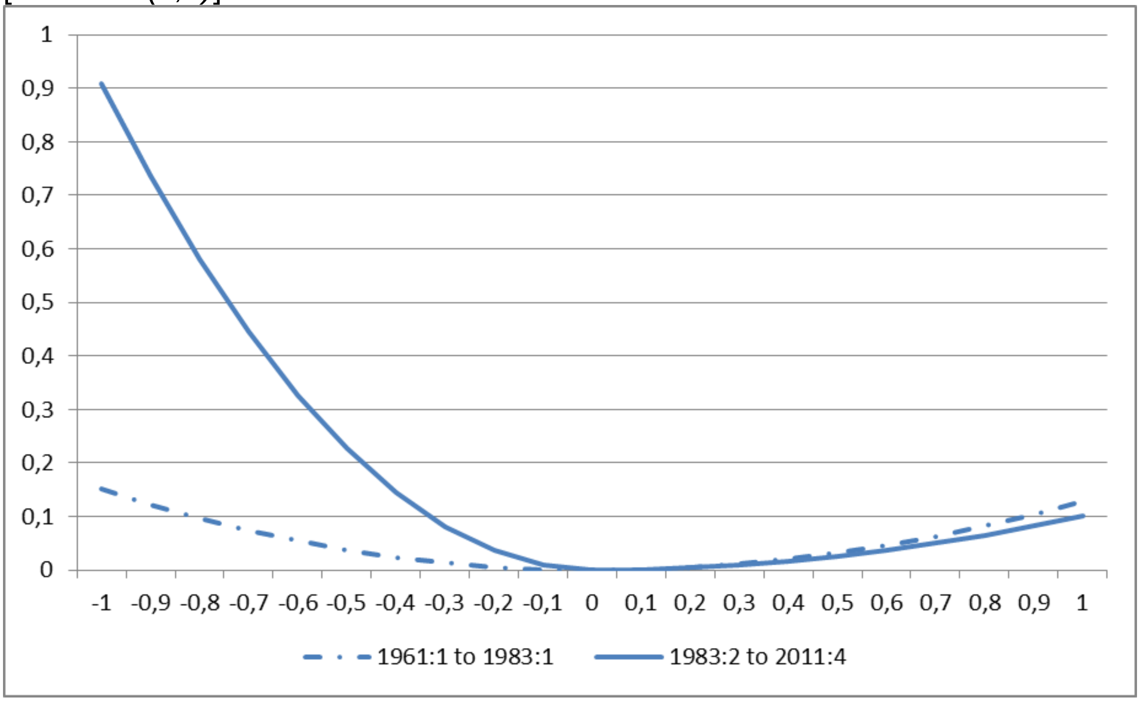
Table 7. Time varying volatility and asymmetric responses of volatility: 1962:1 to 1983:1 and 1983:2 to 2011:4 (regime shifts in the mean in 1983:1 and 1995:4)

	1962:1 to 1983:1		1983:2 to 2011:4	
Parameters	ARMA(1,3)-TGARCH(1,1)	ARMA(1,3)-EGARCH(1,1)	ARMA(4,3)-TGARCH(1,1)	ARMA(4,3)-EGARCH(1,1)
μ	0.07256 (0.492)	0.24285 (0.466)	0.19049 (0.276)	0.07778 (0.279)
ϕ_1	0.48855** (0.068)	0.50551** (0.072)	0.47253** (0.092)	0.54230** (0.072)
θ_1	0.90871** (0.038)	0.89789** (0.033)	0.92835** (0.055)	0.92085** (0.052)
θ_2	0.86731** (0.041)	0.85809** (0.034)	1.02278** (0.028)	0.94237** (0.039)
θ_3	0.95457** (0.025)	0.94991** (0.065)	0.82433** (0.049)	0.82741** (0.050)
ϖ	0.44635 (0.433)	-2.43470** (0.438)	0.10854** (0.037)	3.47123** (0.309)
α_1	0.13876 (1.141)	0.93954* (0.046)	0.07028 (0.204)	0.53793** (0.155)
β_1	0.12827 (0.274)	0.05451 (0.074)	0.10156 (0.0967)	-0.26849** (0.166)
β_2	0.02287 (0.259)	0.35666** (0.147)	0.80727** (0.231)	0.64619** (0.171)
R^2	0.8597	0.8616	0.922	0.925
J-B	1.7304 [0.421]	1.1119 [0.574]	0.389 [0.823]	1.4851 [0.475]
LM ARCH (1)	0.1092 [0.7418]	0.0483 [0.826]	0.1567 [0.693]	0.0312 [0.850]
LM ARCH (5)	0.3243 [0.897]	0.3783 [0.862]	0.7775 [0.568]	0.0531 [0.893]

Source: Authors' calculation. Note: Bollerslev-Wooldridge robust standard errors in square brackets; p-values in brackets; * indicates statistical significance at 10% level; ** indicates statistical significance at 5% level or less.

The corresponding news impact curves, considering the TGARCH specifications, are represented in Figure 6. The analysis is quite informative on some important points. First the leverage effect is not significant over the period from 1962:1 to 1983:1, that is, negative and positive shocks to GDP do not induce impacts of different magnitude on volatility. Second, negative shocks generate significant asymmetric effects on GDP growth volatility in the period from 1983:2 to 2011:4. Negative shocks to GDP growth induce higher volatility than positive shocks of identical magnitude. Therefore, there has been a change of the pattern of impacts in that the leverage effects are statistically significant after 1983. Both the *T-GARCH* and *E-GARCH* estimates point toward an increase of the asymmetric nature of shocks to GDP on volatility. In particular, it is estimated that the impacts of negative shock exceed those of positive shocks by coefficients of 8.95 and 6.37 for the period 1983:2-2011:4, considering, respectively, the *T-GARCH* and the *EGARCH* specifications.

Figure 6. Impacts of positive and negative shocks on GDP growth volatility [*TGARCH(1,1)*]

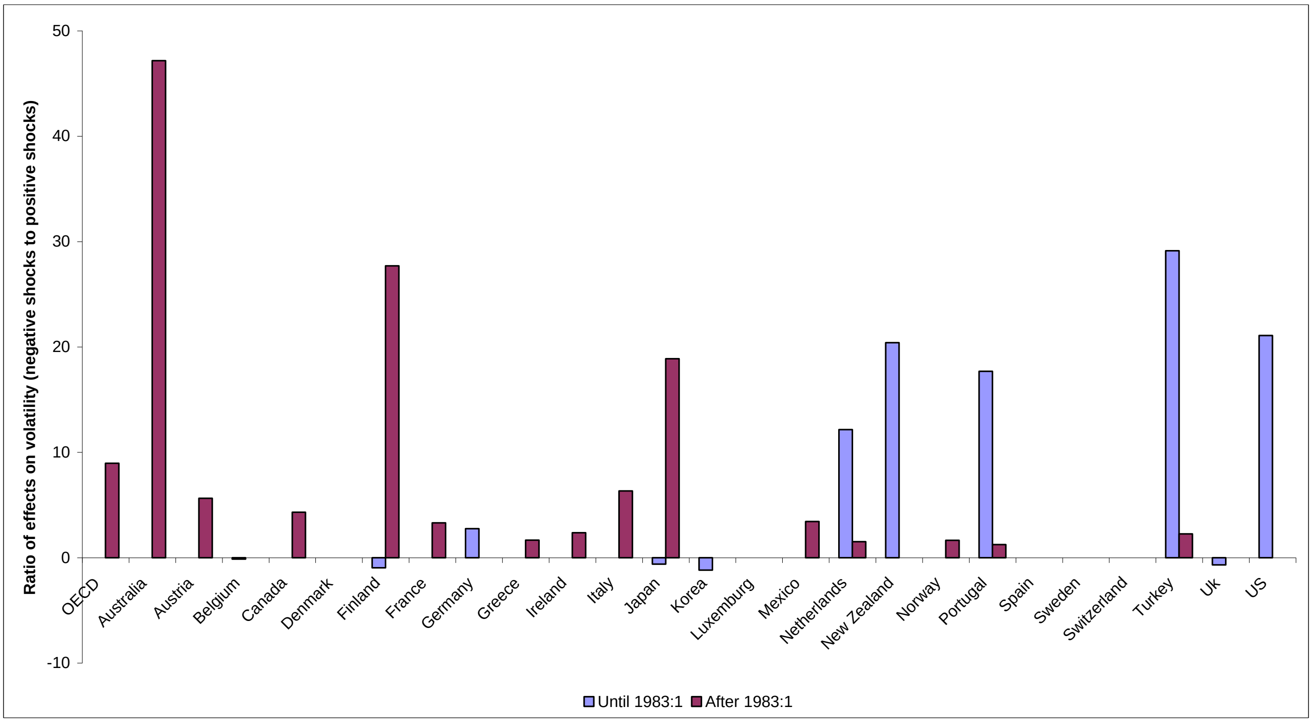


4.6-On the country specific contribution for the volatility asymmetric behaviour

The analysis country by country leads to the following picture on the volatility asymmetric behaviour over the two sub periods, given by Figure 7[4].

[4] Some countries have been excluded from the analysis due to the reduced number of observations. Those are the cases of Chile, Czech Republic, Estonia, Iceland, Israel, Slovak Republic and Slovenia. Details on model specification for each country are given in Annex (Table A1).

Figure 7. Effects of negative shocks relatively to effects of positive shocks on GDP volatility by country



In accordance with the absence of asymmetries evidence at the aggregate level, over the period until 1983:1, we found no evidence of asymmetries of the effects from positive and negative shocks in fifteen countries, namely, Australia, Austria, Belgium, Canada, Denmark, France, Greece, Ireland, Italy, Luxemburg, Mexico, Norway, Spain, Sweden and Switzerland. However, we found evidence of asymmetries with negative shocks causing higher volatility than positive shocks of identical magnitude in six countries, namely Germany, Netherlands, New Zealand, Portugal, Turkey and the US. Finally, in the remaining countries, negative shocks to GDP cause lower volatility than positive shocks of identical magnitude. Those are the cases of Finland, Japan and the UK.

Over the second part of the sample, after 1983:1, the evidence of asymmetries at the aggregate level, with the effects of negative shocks being higher than those of positive shocks of identical magnitude, is sustained by the experiences in Australia, Austria, Canada, Finland, France, Greece, Ireland, Italy, Japan, Mexico, Netherlands, Norway, Portugal and Turkey.

The analysis suggests that some countries more vulnerable to negative shocks before 1983, continue to show higher vulnerability to such shocks after 1983. Those are the cases of the Netherlands, Portugal and Turkey. While countries, such as Australia, Austria, Canada, France, Greece, Ireland, Italy, Mexico, Norway, Finland and Japan, present vulnerability increase to negative shocks after 1983, other report balanced effects from positive and negative shocks. Those are the cases of Belgium, Denmark, Luxemburg, Spain, Sweden, Switzerland, New Zealand, Korea, the US and the UK.

5. Conclusions

This paper investigates the volatility of real GDP growth in the OECD, using quarterly data over the last five decades and it is mainly motivated by the occurrence of "the Great Moderation" phenomenon of volatility declining across almost all the member states. The absence of information on this issue for the OECD at the aggregate level, as well as for the individual member states, together with the lack of consensus in the literature about the behaviour of volatility across the business cycle, attributed mostly by methodological issues, are open points in the research agenda that constitute an opportunity window for this research.

This study adopts a generalized autoregressive conditional heteroskedasticity (*GARCH*) modelling strategy accounting for the occurrence of regime changes in both the trend and volatility of GDP series to identify signs of "the Great Moderation" in the OECD, the time-varying nature of volatility and its symmetric/asymmetric nature across the business cycle and over the sample period.

The results reveal a progressive "moderation" both at the aggregate and disaggregate levels, being characterized by a decline in both GDP growth rates and associated volatility.

Asymmetric behaviour of growth volatility seems to emerge over the business cycle. The results suggest that periods of positive growth are characterized by a positive relationship between growth rates and volatility, while periods of negative growth are characterized by a negative relationship. We estimate that the impacts of negative shocks on volatility exceed those of positive shocks from four to eight times over the sample period. Although, this asymmetric pattern is not stable over time and the time disaggregate analysis uncovers an increasing pattern of the asymmetry, which may provide a sign of increased economic vulnerability to exogenous negative shocks. The increase in the persistence of this asymmetry is particularly observed when the analysis is performed considering 1983:1 as a benchmark date. The equilibrium of the effects caused by positive and negative shocks before 1983 gives place to a disequilibrium with the effects of negative shocks to exceed those of positive shocks by 7.54 and 2.42 depending on the estimated model specification.

The general conclusion points toward the vulnerability increase to negative shocks in Australia, Austria, Canada, France, Greece, Ireland, Italy, Mexico, Norway, Finland and Japan, while other countries, such as Belgium, Denmark, Luxemburg, Spain, Sweden, Switzerland, New Zealand, Korea, the US and the UK have managed to reach an equilibrium of the effects from negative and positive shocks.

References

Ahmed S, Levin A and Wilson BA (2004) Recent U.S. macroeconomic stability: Good policies, good practices, or good luck?. Review of Economics and Statistics 86:824-832

Bai J and Perron P (2003) Computation and analysis of multiple structural change models. Journal of Applied Econometrics 18:1-22

Ben_David D, Lumsdaine R and Papell D (2003) Unit root, post-war slowdowns and lon-run growth: evidence from two structural breaks. Empirical Economics 28(2):303-319

Bhar R and Hamori S (2003) Alternative characterization of the volatility in the growth rate of real GDP. Japan and the World Economy 15:223-231

Black F (1987) Business Cycles and Equilibrium. Basil Blackwell, New York.

Blanchard O and Simon J (2001) The long and large decline in U.S. output volatility. Brookings Papers on Economic Activity 32:135-174

Bodman P (2009) Output volatility in Australia. Applied Economics. doi: 10.1080/00036840701367622

Bollerslev T (1986) Generalized autoregressive conditional heteroskedasticity. Journal of Econometrics 31:307-327

Caporale T and McKiernan B (1996) The relationship between output variability and growth: Evidence from post war U.K. data. Scottish Journal of Political Economy 43:229-236

Caporale T and McKiernan B (1998) The Fischer Black hypothesis: Some time-series evidence. Southern Economic Journal 63:765-771

Christiano LJ (1992) Searching for a break in GNP. Journal of Business and Economic Statistics 10:237-249

Debs A (2001) Testing for a Structural Break in the Volatility of Real GDP Growth in Canada. Bank of Canada Working Paper 2001-9.

Dickey DA and Fuller WA (1979) Distribution of the estimators for autoregressive time series with a unit root. Journal of the American Statistical Association 74:427-431

Dickey DA and Fuller WA (1981) Likelihood ratio statistics for autoregressive time series with a unit root. Econometrica 49:1057-1072

Diebold FX (1986) Comments on modelling the persistence of conditional variance. Econometric Reviews 5:51-56

Engle RF and Bollerslev T (1986). Modelling the persistence of conditional variance. Econometric Reviews 5:1-50

Fountas S, Karanasos M and Mendoza A (2004) Output variability and economic growth: the Japanese case. Bulletin of Economic Research 56:353-363

Glosten LR, Jagannathan R and Runkle D (1994) On the relation between the expected value, and the volatility of the nominal excess return on stocks. Journal of Finance 48:1779-1801

Grier K and Tullock G (1989) An Empirical Analysis of Cross-National Economic Growth, 1951-80. Journal of Monetary Economics 24:259-276

Grier KB and Perry MJ (2000). The effects of real and nominal uncertainty on inflation and output growth: Some GARCH-M evidence. Journal of Applied Econometrics 15:45-58

Hamilton J D and Susmel R (1994) Autoregressive conditional heteroskedasticity and changes in regime. Journal of Econometrics 64:307-333

Hamori S (2000) Volatility of real GDP: Some evidence from the United States, the United Kingdom and Japan. Japan and the World Economy 12:143-152

Henry OT and Olekalns N (2002). The effect of recessions on the relationship between output variability and growth. Southern Economic Journal 68:683-692

Hillebrand E (2005) Neglecting parameter changes in GARCH models. Journal of Econometrics 129:121-138

Ho KY and Tsui AKC (2003) Asymmetric volatility of real GDP: Some evidence from Canada, Japan, the United Kingdom and the United States. Japan and the World Economy 15:437-445

Kim CJ and Nelson CR (1999) Has the U.S. economy become more stable? A Bayesian approach based on a Markov-Switching model of the business cycle. Review of Economics and Statistics 81:1-10

Kim CJ, Nelson CR and Startz R (1998). Testing for mean reversion in heteroskedastic data based on Gibbs sampling augmented randomization. Journal of Empirical Finance 5:131-154

Lamoureux CG and Lastrapes WD (1990) Persistence in variance, structural change and the GARCH model. Journal of Business and Economic Statistics 8:225-234

Leybourne SJ and Newbold P (2003) Spurious rejections by cointegration tests induced by structural breaks. Applied Economics 35(9):1117-1121

Lumsdaine RL and Papell DH (1997) Multiple trend breaks and the unit root hypothesis. Review of Economics and Statistics 79(2):212-218

Martin P and Rogers CA (2000) Long-term growth and short-term economic instability. European Economic Review 44:359-381

McConnell MM and Perez-Quiros G (2000) Output fluctuations in the United States: What has changed since the early 1980's?. American Economic Review 90:1464-1476

Mikosch T and Stărică C (2004) Non-stationarities in financial time series, the long-range dependence, and the IGARCH effects. Review of Economics and Statistics 86:378-390

Mills TC and Wang P (2003) Have output growth rates stabilized? Evidence from the G-7 economies. Scottish Journal of Political Economy 50:232-246

Nelson BB (1991) Conditional heteroskedasticity in asset returns: A new approach. Econometrica 59:347-370

Ng S and Perron P (1995) Unit root tests in ARMA models with data-dependent methods for the selection of the truncation lag. Journal of the American Statistical Association 90:268-281

Nyblom J (1989) Testing for the constancy of parameters over time. Journal of the American Statistical Association 84:223-230

Perron P (1989) The great crash, the oil price shock, and the unit root hypothesis. Econometrica 57(6):1361-1401

Perron P (1997) Further evidence on breaking trend functions in macroeconomic variables. Journal of Econometrics 80(2):355-385

Perron P and Vogelsang TJ (1992) Nonstationarity and level shifts with an application to purchasing power parity. Journal of Business and Economic Statistics 10:301-320

Phillips PCB and Perron P (1988) Testing for a unit root in time series analysis. Biometrica 75:335-346

Ramey G and Ramey V (1995) Cross-Country Evidence on the Link between Volatility and Growth. American Economic Review 85:1138-1151

Speight AEH (1999) U.K. output variability and growth: Some further evidence. Scottish Journal of Political Economy 46:175-184

Stock JH and Watson MW (2003) Has the business cycle changed? Evidence and explanations. In: Federal Reserve Bank of Kansas City (ed.) Proceedings of Monetary Policy and Uncertainty: Adapting to a Changing Economy. Jackson Hole, Wyo., pp 9-56.

Summers PM (2005) What caused the Great Moderation? Some cross-country evidence. Economic Review (Third Quarter)", Federal Reserve Bank of Kansas City, 5-32.

Voss G (2004) Aspects of Canadian and US business cycles. Paper presented for Canada and the Global Economy, Bank of Canada Conference, November 2004.

Zakoian JM (1994) Threshold heteroskedastic model. Journal of Economic Dynamics and Control 18:931-955

Zivot E and Andrews DWK (1992) Further evidence on the great crash, the oil price shock and the unit root hypothesis. Journal of Business and Economics Statistics 10(3):251-270

Annex A

Table A1. Country-specific analysis

Countries	Structural breaks		Model specification	
	Growth rate	Conditional variance	Before 1983:1	After 1983:1
Australia	1984:4; 1993:4	1971:3; 1983:4	ARMA(1,3)	ARMA(1,3)
Austria	1972:4; 2005:4	1969:1; 1987:1	ARMA(1,3)	ARMA(1,3)
Belgium	1974:3; 1987:1	1981:2; 1989:3	ARMA(2,4)	ARMA(2,4)
Canada	1984:4; 1993:4	1984:3; 1993:3	ARMA(1,4)	ARMA(1,3)
Denmark	1983:4; 1993:4	1966:3; 1974:2	ARMA(4,3)	ARMA(0,3)
Finland	1990:2; 2001:2	1990:3; 1998:1	ARMA(1,3)	ARMA(1,3)
France	1974:4; 1997:2	1987:3; 1997:1	ARMA(0,3)	ARMA(2,3)
Germany	1980:2; 1992:4	1973:1; 1987:1	ARMA(4,3)	ARMA(1,3)
Greece	1980:3; 2005:4	1973:2; 1992:4	ARMA(0,3)	ARMA(0,4)
Ireland	1980:2; 1999:1	1994:2; 2004:4	ARMA(2,3)	ARMA(1,4)
Italy	1970:2; 2005:4	1974:3; 2005:4	ARMA(0,3)	ARMA(3,4)
Japan	1973:2; 1991:3	1970:3; 1987:1	ARMA(0,3)	ARMA(1,4)
Korea	1988:1; 2007:1	1979:1; 1991:2	ARMA(0,3)	ARMA(0,3)
Luxemburg	1974:3; 1991:4	1985:3; 1997:1	ARMA(2,0)	ARMA(2,3)
Mexico	1981:4; 2000:3	1989:4; 19996:3	ARMA(1,3)	ARMA(2,3)
Netherlands	1980:2; 2001:1	1983:2; 2005:4	ARMA(0,4)	ARMA(0,3)
New Zealand	1965:4; 1966:4	1965:4; 1992:4	ARMA80,3)	ARMA(2,4)
Norway	1980:2; 1991:4	1993:3; 2004:1	ARMA(3,3)	ARMA(2,4)
Portugal	1976:1; 2004:2	1979:1; 1985:1	ARMA(4,3)	ARMA(4,3)
Spain	1974:4; 1990:4	1986:4; 1996:1	ARMA(4,3)	ARMA(3,4)
Sweden	1988:2; 1998:4	1988:1; 2000:2	ARMA(1,4)	ARMA(1,3
Switzerland	1979:1; 1995:1	1979:1; 1986:2	ARMA(1,3)	ARMA(1,3)
Turkey	2001:4; 2006:3	1983:2; 1992:3	ARMA(1,4)	ARMA(0,4)
UK	1984:4; 1994:2	1983:1; 1993:1	ARMA(1,4)	ARMA(1,3)
US	1978:2; 1983:1	1982:4; 1987:4	ARMA(0,4)	ARMA(2,4)