Structural Breaks and Volatility of
Gross Domestic Product: Evidence for Portugal

Jorge M. Andraz
Faculdade de Economia, Universidade do Algarve, Campus de Gambelas, 8000 Faro, Portugal
CEFAGE-UE– Center for Advanced Studies in Management and Economics,
Universidade de Évora, Évora, Portugal.
Email: jandraz@ualg.pt

Nélia M. Norte
Faculdade de Economia, Universidade do Algarve, Campus de Gambelas, 8000 Faro, Portugal
Email: nnorte@ualg.pt

Abstract
This paper presents an empirical analysis of volatility in GDP real growth rates for Portugal over the period 1960-2010. The objectives of this paper are threefold: (1) to assess the occurrence of “the Great Moderation” in Portugal 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. By adopting GARCH modelling strategy accounting for the occurrence of regime changes in both the trend and volatility, the results reveal a progressive “moderation” in Portugal, characterized by two regime changes in both growth rates and volatility. The results suggest that the impact of negative shocks on volatility exceeds that of positive shocks at least 62.0% over the sample period. However, these asymmetric effects show a decreasing pattern over the sample period, indicating less vulnerability of the economy to exogenous shocks.

JEL Classification: C22, E23, E32.

Key words: GDP, volatility, structural change, business cycles, Portugal.
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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 example, Kim and Nelson (1999), McConnell and Perez-Quiros (2000), Blanchard and Simon (2001), and Ahmed et al. (2004), among others, document a structural change in the volatility of U.S. GDP growth, 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, although the break occurs at different times. 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 a small and open economy like Portugal, 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 Portugal 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.

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. Section 5 reports the main conclusions.

2. BASIC EVIDENCE OF GDP VOLATILITY: DATA, STATISTICS AND UNIT ROOT TESTS
Data sources and descriptive statistics

This paper uses data on quarterly real GDP in Portugal over the period 1960:1-2010:2. 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 Portuguese GDP, 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 to occur in the 1970s, and a possible second change by the end of the 1990s.

[Figure 1 here]

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

\[
y_t = \left( \ln Y_t - \ln Y_{t-4} \right) \times 100,
\]

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. After the high and increasing growth phase of the 1960s, Portuguese GDP growth enacted a lower average growth phase since the mid-1970s, notwithstanding the occurrence of up- and downswings in the 80s and the 90s. Important remarks are also pointed to the quarter fluctuations, which also appear to have diminished over time. The variation bands also indicate possible major shifts contemporaneous with the trend shifts.

[Figure 2 here]

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 3.53%, with maximum and minimum values of 11.34% in 1973:2 and -6.51% in 1975:1, while the output volatility, represented by the standard deviation, was 3.33.

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 5.88% per annum in the 60s and 5.06% in the 70s reduced to 3.16% in the 80s, 2.97% in the 90s and 0.94% between 2000 and 2010. The results also
illustrate the significant decline in real GDP volatility since the late 1970s. The standard deviation reduced from 4.54 over the 1970s to 2.96 over the 1980s, 2.01 over the 1990s and finally 1.89 over the last decade.

Bearing in mind the possible break dates on trend and volatility in the mid 70s and around 2001, Panel C reports consecutive reductions of the annual average growth from 6.25% before 1974 to 2.52% afterwards and from 4.22% in the period 1961-2000 to 0.64% in the following period. In the same vein, volatility reported a reduction from 3.23% to 2.54% and from 3.30% to 1.89%, respectively.

[Table 1 here]

Therefore, the analysis clearly illustrates the occurrence of the “Great Moderation” phenomenon in Portugal, by the end of the 70s. A variety of explanations, not exclusive for Portugal, 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. In the particular case of Portugal, the suggested dates for the breaks occurrence are coincident with major structural changes motivated by domestic and international events. While the first break in the mid-1970s is coincident with external and internal perturbations motivated by the oil shocks and the democratization of the Portuguese economy that emerged from the revolution of April 1974, the second date, by the end of the 1990s, is coincident with the currency change from the Portuguese Escudo to the Euro.

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), the permanent fall in average GDP growth in the 70s in Portugal from around 5% per annum to just over 3% per annum 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 the Portuguese GDP growth has gone through fluctuations in trend and volatility much in the same way as in other countries, which should not be neglected in the analysis that follows.

*Unit root tests*

In this subsection we analyze 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.

[Table 2 here]

3. METHODOLOGICAL FRAMEWORK

*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

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1 The analysis was also performed by using White’s heteroscedasticity-consistent standard errors. The conclusion on the rejection of a unit root remain unchanged.
clearly suggested the possible existence of two structural breaks in the GDP growth rates around the mid 70s and by the end of 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

\[
\Delta y_t = \mu + \beta t + \theta DU1_t + \gamma DT1_t + \sigma DU2_t + \psi DT2_t + \alpha y_{t-1} + \sum_{i=1}^{k} c_i \Delta y_{t-i} + \varepsilon_t
\]  

(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 \( DU_1 \) and \( DU_2 \) capture structural changes in the intercept at time \( TBI \) and \( TB2 \) respectively. The other two dummy variables, i.e., \( DT_1 \) and \( DT_2 \), capture shifts in the trend variable at time \( TBI \) 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 \( TBI \) and \( TB2 \), cover the \( 0.05T \) – \( 0.95T \) period. We have selected the break points (\( TBI \) and \( TB2 \)) based on the minimum value of the \( t \) statistic for \( \alpha \). 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 \( \alpha = 0 \) in Equation (2), which implies that there is a unit root in \( y_t \). The alternative hypothesis is that \( \alpha < 0 \), which implies that \( y_t \) is breakpoint stationary.

**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,

\[
\Phi(L)y_t = \mu + \Theta(L)u_t + \delta h_t \quad (3)
\]

\[
B(L)h_t = \sigma + A(L)u_t^2 \quad (4)
\]

where,

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

Let \( \{u_t\} \) be a real-valued time series stochastic process generated by \( u_t = e_t \sqrt{h_t} \), 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 \( \sum_{i=1}^{\infty} \) which in turn is the sigma-algebra generated by \( \{u_{t-1}, u_{t-2}, \ldots\} \). That
is, $h_t$ is the conditional variance of the errors $\{u_t\}$, $\left(u_t \sum_{t-1}^\infty \right) \sim (0, h_t)$. 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,

$$B(L)h_t = \alpha + A(L)u_t^2 + C(L)\bar{u}_t^2$$  \hspace{1cm} (5)

where $C(L) = \sum_{i=1}^{q} \beta_{i+1} I_{t-i} L^i$ 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 $u_{t-1} > 0$ have an impact of $\alpha_t$, bad news, expressed by $u_{t-1} < 0$ have an impact of $\alpha_t + \sum_{i=1}^{q} \beta_{i+1}$. 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:

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

$$z_{t-i} = \beta_1 \frac{u_{t-i}}{\sqrt{h_{t-i}}} + \beta_2 \left[ \frac{u_{t-i}}{\sqrt{h_{t-i}}} - E \left[ \frac{u_{t-i}}{\sqrt{h_{t-i}}} \right] \right],$$  \hspace{1cm} (6)
where \( C(L) = \sum_{i=1}^{d} c_i L^i \) 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.

**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 2005:2. 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 1976:1 and 2004:2. The estimated coefficients for \( \theta \), \( \gamma \) and \( \psi \) are significant, indicating that structural changes have impacted on both the intercept and trend. 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 1979:1 and 1985:1. Once again, the coefficients of the dummy variables report statistically significant impacts of structural changes on both the intercept and trend.

[Table 3 here]

**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 3. By visual inspection is perceptible a break in the beginning of the 80s, which mask the two breaks detected by the LP test.

[Figure 3 here]

The changes appear to be of one-off major shifts type, instead of being gradual over time. Further visual evidence can be provided by obtaining the rolling averages of standard deviations of the absolute demeaned GDP growth series with a given periodicity. Figure 4 displays the scenario with 4 quarter rolling averages\(^2\) and it is perceptible the abrupt decline around the predicted dates.

[Figure 4 here]

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: \[
\Phi(L)y_t = \mu + u_t
\] (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 5\(^{th}\) 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%.

\(^2\) The results are robust to any change of time periodicity.
\(^3\) The results are not provided here but are available upon request.
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

\[
\sigma_i^2 = \mu + \Theta(L)\mu_i^2 + v_i
\]  

(9)

where \( \Theta(L) = 1 - \sum_{i=1}^{5} \phi_i L^i \)

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 1979:1 and 1985:1, are included in the model, as follows:

\[
\sigma_i^2 = \beta_0 + \Theta(L)\mu_i^2 + \rho_1 DT1 + \rho_2 DT2 + \theta_i
\]  

(10)

The results, in the third column, report no evidence of instability in any parameter, which is suggestive of significant shifts to lower volatility regimes over the 80s, being captured by binary dummy variables. The negative values of the \( \rho \) parameters suggest a shift from high variance to low variance regimes.

[Table 4 here]

**GARCH modelling: features of GDP growth volatility over 1961:1 to 2010:2**

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 here]
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 1976:1 and 2004:2. Following standard Box-Jenkins ARIMA modelling procedure, and considering the model selection criteria, Portuguese GDP growth is best modelled as an ARMA(3,4) (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 Jarque-Bera test indicates that the residuals exhibit non-normality and the Ljung-Box tests indicate that whilst there is no significant autocorrelation remaining in the levels of the residuals, 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 here]

To address these inequacies and allow for time varying conditional variances, a \( GARCH(p,q) \) modelling procedure of the squared residuals was implemented. The best (lowest AIC and SBC best residuals diagnostics) specification includes a highly significant deterministic shift dummy in the variance term of a \( ARMA(3,4)_{-}GARCH(1,1)-M \) specification, in which there is feedback from the conditional variance to the conditional mean. The corresponding results are reported in Table 6 (column 1) along with the residuals diagnostic tests. The coefficients’ estimates in the conditional mean specification are still significant at the 5% or, at least, the 10% levels. The coefficient of the conditional variance is positive as expected, suggesting that the higher volatility contributes to higher mean values. Regarding the conditional variance specification, the process stability is guaranteed and the long-run volatility is 1.21%. The coefficients on both the lagged square residual and lagged conditional variance terms in the conditional variance equation are also highly statistically significant, and 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 here]

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, in 1974, 1975, 1984, 1993, 2003 and 2009. As these years coincide with recessions of the Portuguese economy, it seems that the asymmetry of the business cycle may account for part of the increase in measured volatility during recessions.

[Figure 5 here]

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, but the EGARCH specification seems to perform better than the TGARCH, as the former yields the highest log-likelihood and the lowest AIC and SIC values. The leverage effect estimated in the TGARCH is positive, which postulates that while the impact of good news on variance is 0.389, the impact of bad news exceeds that of good news in about 62.0%,
corresponding to an impact of 0.629. Considering the EGARCH model estimates, the magnitude effect is again positive, corresponding to 0.241, while the leverage effect is negative, corresponding to -0.108. Once again, the asymmetric effects are confirmed with the impact of negative shocks being more than twice 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 causes asymmetries of the corresponding news impact curves.

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 1985:1, considering parsimonious specifications (lowest AIC and SIC) are reported in Table 7. The corresponding news impact curves, considering both asymmetric specifications, are represented in Figures 6 and 7. The analysis is quite informative on some important points. First, positive and negative shocks generate asymmetric effects on GDP growth volatility in both periods. Negative shocks to GDP growth induce higher volatility than positive shocks of identical magnitude. Second, there has been a change of the pattern of impacts in that the leverage effects are not statistically significant after 1985. The T-GARCH and E-GARCH estimates point toward a decline 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 17.68 and 1.58, respectively, for the period 1961:1-1985:1 and 1.24 and 1.05 for the period 1985:2-2010:2.

5. CONCLUSIONS

This paper investigates the volatility of real GDP growth in Portugal, 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 several countries. The absence of information on this issue in the case of Portugal and also 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 Portugal, 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” in Portugal, being characterized by a decline in both GDP growth rates and associated volatility. The association of phenomenon with the occurrence of important events at the national and international levels is inevitable. At the national level, the democratization process of the Portuguese economy enacted after the April’74 Revolution, the political instability that followed, the adhesion to the European Union (former European Economic Community), and the currency change, together with the economy’s high vulnerability to the unavoidable external oil shocks (among others) have been in the origin of this scenario. Altogether, they have originated deep effects on the economy and jointly contributed for the occurrence of structural changes in 1976 and 2004 on the growth rates and 1979 and 1985 on the 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 impact of negative shocks on volatility exceeds that of positive shocks at least 62.0% over the sample period. Although, this asymmetric pattern is not stable over time and the time disaggregate analysis uncovers a decreasing pattern of the asymmetry, which may provide a sign of less economic vulnerability to exogenous shocks. The decline in the persistence of this asymmetry is particularly observed when the analysis is performed considering 1985:1 as a benchmark date. The ratio of the effects of negative shocks to positive shocks declines from 17.68 to 1.24 and from 2.47 to 1.57 depending on the estimated model specification.
REFERENCES


Figure 1: Portuguese GDP 1960:1-2010:2

Source: OECD data and authors’ calculation.

Figure 2: Preliminary evidence on trend and volatility of Portuguese real GDP growth:
1961:1-2010:2

Source: OECD and authors’ calculation.
Table 1: Summary statistics of real growth rates

Panel A: general statistics for the sample period

<table>
<thead>
<tr>
<th>Period</th>
<th>Mean</th>
<th>Median</th>
<th>Maximum</th>
<th>Minimum</th>
</tr>
</thead>
<tbody>
<tr>
<td>1961:1-2010:2</td>
<td>3.53%</td>
<td>3.49%</td>
<td>11.34%</td>
<td>-6.51%</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>St. Dev.: 3.33</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Panel B: moment statistics by decade

<table>
<thead>
<tr>
<th>Period</th>
<th>Sample mean (%)</th>
<th>Sample standard deviation</th>
</tr>
</thead>
<tbody>
<tr>
<td>1961:1 – 1969:4</td>
<td>5.884</td>
<td>2.037</td>
</tr>
<tr>
<td>1990:1 – 1999:4</td>
<td>2.969</td>
<td>2.010</td>
</tr>
<tr>
<td>2000:1 – 2010:2</td>
<td>0.942</td>
<td>1.890</td>
</tr>
</tbody>
</table>

Panel C: evidence of decline of moment statistics

<table>
<thead>
<tr>
<th>Period</th>
<th>Sample mean (%)</th>
<th>Sample standard deviation</th>
</tr>
</thead>
<tbody>
<tr>
<td>1975:1 – 2010:2</td>
<td>2.518</td>
<td>2.536</td>
</tr>
<tr>
<td>2001:1 – 2010:2</td>
<td>0.636</td>
<td>1.890</td>
</tr>
</tbody>
</table>

Source: OECD and authors’ calculation.

Table 2: Unit root tests

<table>
<thead>
<tr>
<th></th>
<th>AFD</th>
<th>DF GLS (ERS)</th>
<th>PP</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>-3.312*</td>
<td>-4.3419*</td>
<td>3.223*</td>
<td>-3.994*</td>
</tr>
<tr>
<td>[0.0156]</td>
<td>[0.0034]</td>
<td>[0.0023]</td>
<td>[0.0004]</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th></th>
<th>Constant and trend</th>
<th>Constant and trend</th>
<th>Constant and trend</th>
</tr>
</thead>
<tbody>
<tr>
<td>-3.992*</td>
<td>-4.7108*</td>
<td></td>
<td></td>
</tr>
<tr>
<td>[0.0018]</td>
<td>[0.0009]</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Note: * indicates statistical significant values; p-values in brackets; the critical values of the PP DF-GLS test considering a constant term in the regression are -2.577 (1%), -1.942 (5%) and -1.615 (10%). Considering a constant and a time trend: -3.468(1%), -2.937 (5%) and -2.647 (10%).
Table 3: Lumsdaine and Papell test for structural changes

<table>
<thead>
<tr>
<th>Real GDP growth</th>
<th>( TB1 )</th>
<th>( TB2 )</th>
<th>( \mu )</th>
<th>( \beta )</th>
<th>( \theta )</th>
<th>( \Gamma )</th>
<th>( \omega )</th>
<th>( \psi )</th>
<th>( \alpha )</th>
<th>( K )</th>
</tr>
</thead>
<tbody>
<tr>
<td>Conditional mean</td>
<td>1976:1</td>
<td>2004:2</td>
<td>1.358*</td>
<td>0.002*</td>
<td>0.012*</td>
<td>-0.001*</td>
<td>0.0069</td>
<td>-0.001*</td>
<td>-0.133*</td>
<td>6</td>
</tr>
<tr>
<td>Conditional standard deviation (breaks in the mean)</td>
<td>1979:1</td>
<td>1985:1</td>
<td>0.004 (0.01)</td>
<td>0.016 (1.09)</td>
<td>-2.895* (-4.01)</td>
<td>-1.672* (-2.98)</td>
<td>0.138* (3.34)</td>
<td>-0.154* (-3.87)</td>
<td>-0.289* (-8.95)</td>
<td>8</td>
</tr>
</tbody>
</table>

Source: Authors’ calculation.

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

Equation specification: \( \Delta y_t = \mu + \beta t + \theta DU1 + \gamma DT1 + \omega DU2 + \psi DT2 + \alpha y_{t-1} + \sum_{i=1}^{K} \Delta y_{t-i} + \epsilon_t \)

Figure 3: Portuguese GDP growth rate volatility 1960:1-2010:2

Source: OECD and authors’ calculation.
Figure 4: The nature of breaks in the Portuguese GDP growth rates

![Graph showing the nature of breaks in the Portuguese GDP growth rates.]

Source: OECD and authors’ calculation.

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

<table>
<thead>
<tr>
<th>Parameters</th>
<th>Model 1</th>
<th>Model 2</th>
<th>Model 3</th>
<th>5% critical values</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \mu )</td>
<td>1.080</td>
<td>0.652</td>
<td>0.117</td>
<td>0.47</td>
</tr>
<tr>
<td>( \phi_1 )</td>
<td>0.163</td>
<td>0.048</td>
<td>0.034</td>
<td>0.47</td>
</tr>
<tr>
<td>( \phi_2 )</td>
<td>0.315</td>
<td>0.086</td>
<td>0.026</td>
<td>0.47</td>
</tr>
<tr>
<td>( \phi_3 )</td>
<td>0.446</td>
<td>0.101</td>
<td>0.021</td>
<td>0.47</td>
</tr>
<tr>
<td>( \phi_4 )</td>
<td>0.259</td>
<td>0.191</td>
<td>0.039</td>
<td>0.47</td>
</tr>
<tr>
<td>( \phi_5 )</td>
<td>0.216</td>
<td>0.173</td>
<td>0.059</td>
<td>0.47</td>
</tr>
<tr>
<td>( \rho_1 )</td>
<td></td>
<td>-0.484</td>
<td></td>
<td>0.47</td>
</tr>
<tr>
<td>( \rho_2 )</td>
<td></td>
<td>-0.671</td>
<td></td>
<td>0.47</td>
</tr>
<tr>
<td>( \sigma^2 )</td>
<td>0.561*</td>
<td>1.065*</td>
<td>0.079*</td>
<td>0.47</td>
</tr>
<tr>
<td>Joint Lc</td>
<td>2.804*</td>
<td>1.738*</td>
<td>1.018</td>
<td>(5% critical values)</td>
</tr>
<tr>
<td>(1.90)</td>
<td>(1.68)</td>
<td>(1.68)</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

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.
Figure 5: Portuguese 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.

Table 5: ARMA model of Portuguese Filtered GDP growth: 1960-2010
(regime shifts in the mean in 1976:1 and 2004:2)

\[
y_t = -0.04032 + 1.02782 y_{t-1} + 0.31631 y_{t-2} - 0.42999 y_{t-3} - 0.01912 \varepsilon_{t-1} - 0.20925 \varepsilon_{t-2} \\
+ 0.00362 \varepsilon_{t-3} - 0.77482 \varepsilon_{t-4} \\
(0.075) \\
(0.074) \\
(0.108) \\
(0.073) \\
(0.056) \\
(0.054) \\
(0.053) \\
(0.055)
\]

<table>
<thead>
<tr>
<th>$R^2$</th>
<th>0.843</th>
</tr>
</thead>
<tbody>
<tr>
<td>$LM - test(2)$</td>
<td>0.490 [0.613]</td>
</tr>
<tr>
<td>Jarque - Bera</td>
<td>7.986 [0.018]</td>
</tr>
<tr>
<td>$Q(10)$</td>
<td>3.623 [0.305]</td>
</tr>
<tr>
<td>$Q(15)$</td>
<td>8.697 [0.369]</td>
</tr>
<tr>
<td>$Q^2(10)$</td>
<td>28.030 [0.000]</td>
</tr>
<tr>
<td>$Q^2(15)$</td>
<td>42.932 [0.000]</td>
</tr>
<tr>
<td>$LM - ARCH(1)$</td>
<td>13.304 [0.000]</td>
</tr>
<tr>
<td>$LM - ARCH(5)$</td>
<td>5.128 [0.000]</td>
</tr>
<tr>
<td>$BDS(3,1)$</td>
<td>0.047 [0.000]</td>
</tr>
<tr>
<td>$BDS(5,1.5)$</td>
<td>0.063 [0.000]</td>
</tr>
</tbody>
</table>

Source: Authors’ calculation.
Note: standard errors in square brackets and p-values in brackets;
Table 6: Time varying volatility and asymmetric responses of volatility: 1960-2010
(regime shifts in the mean in 1976:1 and 2004:2)

<table>
<thead>
<tr>
<th>Parameters</th>
<th>ARMA(3,4)-GARCH(1,1)-M</th>
<th>ARMA(3,4)-TGARCH(1,1)-M</th>
<th>ARMA(3,4)-EGARCH(1,1)-M</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\mu$</td>
<td>1.21285 (0.499)</td>
<td>0.27884 (0.169)</td>
<td>0.28134 (0.181)</td>
</tr>
<tr>
<td>$\phi_1$</td>
<td>-0.25063 (0.104)</td>
<td>1.10068 (0.095)</td>
<td>1.07190 (0.104)</td>
</tr>
<tr>
<td>$\phi_2$</td>
<td>0.27051 (0.070)</td>
<td>0.06017 (0.151)</td>
<td>0.06986 (0.137)</td>
</tr>
<tr>
<td>$\phi_3$</td>
<td>0.09936 (0.057)</td>
<td>-0.28816 (0.084)</td>
<td>-0.32374 (0.069)</td>
</tr>
<tr>
<td>$\theta_1$</td>
<td>1.26741 (0.033)</td>
<td>0.03539 (0.077)</td>
<td>0.08025 (0.084)</td>
</tr>
<tr>
<td>$\theta_2$</td>
<td>1.21354 (0.030)</td>
<td>-0.06558 (0.064)</td>
<td>-0.04039 (0.080)</td>
</tr>
<tr>
<td>$\theta_3$</td>
<td>1.12427 (0.030)</td>
<td>-0.00614 (0.051)</td>
<td>0.11704 (0.083)</td>
</tr>
<tr>
<td>$\theta_4$</td>
<td>0.23588 (0.013)</td>
<td>-0.71439 (0.048)</td>
<td>-0.59804 (0.079)</td>
</tr>
<tr>
<td>$\delta$</td>
<td>0.02291 (0.007)</td>
<td>0.01364 (0.051)</td>
<td>0.03342 (0.005)</td>
</tr>
<tr>
<td>$\sigma$</td>
<td>0.85750 (0.294)</td>
<td>0.29774 (0.003)</td>
<td>-0.13989 (0.053)</td>
</tr>
<tr>
<td>$\alpha_1$</td>
<td>0.32952 (0.132)</td>
<td>0.38959 (0.098)</td>
<td>0.95077 (0.014)</td>
</tr>
<tr>
<td>$\beta_1$</td>
<td>0.17476 (0.054)</td>
<td>0.24125 (0.066)</td>
<td>-0.3149* (0.013)</td>
</tr>
<tr>
<td>$\beta_2$</td>
<td>0.08832 (0.021)</td>
<td>0.24004 (0.137)</td>
<td>-0.10811* (0.064)</td>
</tr>
<tr>
<td>$\psi$</td>
<td>-0.09091 (0.027)</td>
<td>0.01364 (0.005)</td>
<td>-0.03149* (0.013)</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.836</td>
<td>0.836</td>
<td>0.831</td>
</tr>
<tr>
<td>$J-B$</td>
<td>1.406</td>
<td>2.115</td>
<td>3.332</td>
</tr>
<tr>
<td>$LM ARCH (1)$</td>
<td>0.009</td>
<td>1.185</td>
<td>1.269</td>
</tr>
<tr>
<td>$LM ARCH (5)$</td>
<td>0.545</td>
<td>0.997</td>
<td>0.461</td>
</tr>
<tr>
<td>$BDS (3,1)$</td>
<td>0.006</td>
<td>0.013</td>
<td>0.010</td>
</tr>
<tr>
<td>$BDS (5,1.5)$</td>
<td>0.010</td>
<td>0.008</td>
<td>0.008</td>
</tr>
</tbody>
</table>

Source: Authors’ calculation.
Note: Bollerslev-Wooldridge robust standard errors in square brackets; p-values in brackets; * and ** indicate statistical significance at the 5% and 10% levels, respectively.

Model ARMA(3,4)-M: \[1 - \sum_{j=1}^{3} \phi_j L^j \] \[y_t = \mu + \sum_{j=1}^{4} \theta_j L^j u_t + \delta h_t\]

Model ARMA(3,4)-GARCH(1,1)-M: \[1 - \beta_1 L \] \[h_t = \omega + \alpha_1 L u_t^2 + \psi DT_t\]

Model ARMA(3,4)-TGARCH(1,1)-M: \[1 - \beta_1 L \] \[h_t = \omega + \alpha_1 L u_t^2 + \beta_2 L_{t-1} L u_{t-1}^2 + \psi DT_t\]

Model ARMA(3,4)-EGARCH(1,1)-M: \(1 - \alpha_1 L \) \[ln(h_t) = \omega + \varepsilon_{t-1} + \psi DT_t\]

DT is a dummy variable: DT=0 before 1985:1; DT=1 from 1985:1 onwards.

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<table>
<thead>
<tr>
<th>Parameters</th>
<th>1961:1 to 1985:1</th>
<th>1985:2 to 2010:2</th>
</tr>
</thead>
<tbody>
<tr>
<td>ARMA(4,3)- EGARCH(1,1)-M</td>
<td>ARMA(4,3)- EGARCH(1,1)-M</td>
<td>ARMA(4,3)- EGARCH(1,1)</td>
</tr>
<tr>
<td>( \mu )</td>
<td>-0.03611 (0.268)</td>
<td>-0.17636 (0.143)</td>
</tr>
<tr>
<td>( \phi_1 )</td>
<td>0.53340 (0.093)</td>
<td>0.42536 (0.047)</td>
</tr>
<tr>
<td>( \phi_2 )</td>
<td>-0.01239 (0.079)</td>
<td>0.02676 (0.042)</td>
</tr>
<tr>
<td>( \phi_3 )</td>
<td>0.26435 (0.071)</td>
<td>0.27873 (0.035)</td>
</tr>
<tr>
<td>( \phi_4 )</td>
<td>-0.52142* (0.049)</td>
<td>-0.47609* (0.036)</td>
</tr>
<tr>
<td>( \theta_1 )</td>
<td>0.60037 (0.149)</td>
<td>0.75556 (0.074)</td>
</tr>
<tr>
<td>( \theta_2 )</td>
<td>0.92803* (0.051)</td>
<td>0.99897* (0.032)</td>
</tr>
<tr>
<td>( \theta_3 )</td>
<td>0.20013 (0.133)</td>
<td>0.32511 (0.065)</td>
</tr>
<tr>
<td>( \delta )</td>
<td>-0.10332* (0.045)</td>
<td>-0.08646 (0.023)</td>
</tr>
<tr>
<td>( \sigma )</td>
<td>-0.01303* (0.008)</td>
<td>-1.66399 (0.143)</td>
</tr>
<tr>
<td>( \beta_1 )</td>
<td>1.00175 (0.297)</td>
<td>-0.45348 (0.107)</td>
</tr>
<tr>
<td>( \beta_2 )</td>
<td>2.1544 (0.905)</td>
<td>2.02385 (0.186)</td>
</tr>
<tr>
<td>( \alpha_1 )</td>
<td>0.12911 (0.056)</td>
<td>0.76377 (0.056)</td>
</tr>
<tr>
<td>( R^2 )</td>
<td>0.8597</td>
<td>0.8616</td>
</tr>
<tr>
<td>J-B</td>
<td>1.7304 [0.421]</td>
<td>1.1119 [0.574]</td>
</tr>
<tr>
<td>LM ARCH (1)</td>
<td>0.0192 [0.7418]</td>
<td>0.0483 [0.826]</td>
</tr>
<tr>
<td>LM ARCH (5)</td>
<td>0.3243 [0.897]</td>
<td>0.3783 [0.862]</td>
</tr>
<tr>
<td>BDS (3,1)</td>
<td>-0.105 [0.288]</td>
<td>-0.0075 [0.498]</td>
</tr>
<tr>
<td>BDS (5,1.5)</td>
<td>-0.0269 [0.122]</td>
<td>-0.0284 [0.111]</td>
</tr>
</tbody>
</table>

Source: Authors’ calculation.
Note: Bollerslev-Wooldridge robust standard errors in square brackets; p-values in brackets. * and ** indicate statistical significance at the 5% and 10% levels, respectively.
Figure 6: Impacts of positive and negative shocks on GDP growth volatility \[TGARCH(1,1)\]

Figure 7: Impacts of positive and negative shocks on GDP growth volatility \[EGARCH(1,1)\]