Does the Great Recession imply the end of the Great Moderation? International evidence

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Amélie Charles*
Olivier Darné**
Laurent Ferrara***

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(*) School of Management - Audencia Nantes
(**) LEMNA - Université de Nantes
(***) Banque de France et EconomiX, Université Paris Ouest La Défense

INSTITUT d'ECONOMIE et de MANAGEMENT de NANTES - IAE

Laboratoire d'Economie et de Management Nantes-Atlantique
Université de Nantes
Chemin de la Censive du Tertre – BP 52231
44322 Nantes cedex 3 – France
www.univ-nantes.fr/iemn-iae/recherche
Tél. +33 (0)2 40 14 17 17 – Fax +33 (0)2 40 14 17 49

UNIVERSITÉ DE NANTES

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Amélie CHARLES†
Audencia Nantes, School of Management

Olivier DARNÉ‡
LEMNA, University of Nantes

Laurent FERRARA§
Banque de France and
EconomiX, University Paris Ouest La Défense

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†Audencia Nantes, School of Management, 8 route de la Jonelière, 44312 Nantes Cedex 3. Email: acharles@audencia.com.

‡Corresponding author: LEMNA, University of Nantes, IEMN–IAE, Chemin de la Censive du Tertre, BP 52231, 44322 Nantes, France. Email: olivier.darne@univ-nantes.fr.

§EconomiX, University Paris Ouest La Défense, and Banque de France, International Macroeconomics Division. Email: laurent.ferrara@banque-france.fr.

Abstract

After years of low macroeconomic volatility since the early eighties, well documented and referred to as the Great Moderation period in the literature, the 2008-2009 worldwide recession adversely impacted output levels in most of advanced countries. This Great Recession period was characterized by a sharp apparent increase in output volatility. In this paper we evaluate whether this sudden event is likely to be temporary. Whether or not this new volatility regime is likely to persist would have strong macroeconomic effects, especially on business cycles. Based on break detection methods applied to a set of advanced countries, our empirical results do not give evidence to the end of the Great Moderation period but rather that the Great Recession is characterized by a dramatic temporary effect on the output growth but not on its volatility. In addition, we show that neglecting those breaks both in mean and in variance can have large effects on output volatility modelling. Last we empirically show that observed breaks during the Great Recession are to some extent related to uncertainty measures.

Keywords: Great Recession; Great Moderation; breaks; volatility; uncertainty

JEL Classification: E32; C22

1 Introduction

Over the past 30 years, macroeconomic volatility has declined substantially in most developed countries, characterized in the literature as "The Great Moderation" period. This decline in output volatility captured the attention of macroeconomists, especially because it occurred in numerous developed countries, although the timing and details differ from one country to the other. Among the huge empirical literature on this topic, Kim and Nelson (1999), McConnell and Perez-Quiros (2000), Blanchard and Simon (2001), Stock and Watson (2003), Ahmed et al. (2004) and Bernanke (2004), among others, document a structural change in the volatility of US GDP growth, finding a rather dramatic reduction in GDP volatility since the early eighties. As regards other advanced countries, Mills and Wang (2003), Summers (2005), Stock and Watson (2005), Fang et al. (2008), and Smith and Summers (2010) discover a structural break in the volatility of the output growth rate for the G7 countries, although the break occurred at different times. At a more global level, Cecchetti et al. (2006) examine shifts in the volatility of output growth in 25 advanced and emerging countries and find at least one break in all but nine countries and at most two breaks in six of the 25 countries.

Among the potential factors of this Great Moderation period, the literature put forward (i) 'good practices', i.e.: improved inventory management (e.g., McConnell and Perez-Quiros, 2000); (ii) 'good policies', i.e.: good monetary policy (e.g., Clarida et al., 2000; Bernanke, 2004; Boivin and Giannoni, 2006; Gali and Gambetti, 2009); and (iii) 'good luck', i.e.: a decline in the volatility of exogenous shocks (e.g., Stock and Watson, 2003, 2005; Ahmed et al., 2004).

However, after years of moderate volatility in output, the recent " Great Recession" throughout the years 2008 and 2009, that affected most of the advanced countries, as well as some emerging countries, in the wake of the global financial crisis, has strongly surprised macroeconomists by its large amplitude.[1] Among the various explanations of this unexpected severity, Stock and Watson (2012) argue that the macroeconomic shocks were much larger than previously experienced, at least for the US, especially the shocks associated with financial disruptions and heightened uncertainty. This large

[1]Reinhart and Rogoff (2009) call the period of the Great Recession and its aftermath as the Second Great Contraction, where the First Great Contraction was the Great Depression, whereas Hall (2011) calls this period as the Great Slump.

shocks hypothesis is also supported in a sense by Ferrara et al. (2013) who show that the Great Moderation does not come with an increase of the non-linear dynamics within macroeconomic variables, suggesting thus that a linear behaviour with shocks may be more appropriate to describe this specific period of time. Some authors also put forward the major accelerating role of international trade (see Baldwin, 2009), that contributed to the deepness and the worldwide synchronization of this phenomenon.

A policy-relevant issue is to know whether this Great Recession implies the definitive end of the Great Moderation period or if it can be considered as a short-lived phenomenon with no medium-to-long term impact on the macroeconomic volatility. Indeed if we assume that we entered a new era of high macroeconomic volatility, in conjunction with a new era of lower potential growth (which seems to be case for many advanced countries, although this is currently a highly debated issue, see e.g. the recent paper by Reifschneider et al., 2013, as regards the US economy), thus this would lead to more frequent recessions, as defined in the NBER sense, i.e. a prolonged and substantial decline in the aggregate level of output.

Modelling volatility is challenging for econometricians as it is typically an unobserved phenomena, however with some well known stylized facts. For example, as shown by Fernández-Villaverde and Rubio-Ramírez (2010), time-varying volatility, namely periods of high volatility followed by periods of low volatility, is an important feature of macroeconomic times series. To describe fluctuations in volatility, researchers frequently employ some form of generalized autoregressive conditional heteroskedasticity (GARCH) models developed by Engle (1982) and Bollerslev (1986) under the assumption of a stable variance process. Typically, a high degree of persistence in conditional macroeconomic volatility is found in empirical studies. However, it has been also proved that this persistence if often driven by the neglecting of breaks in the variance (see, e.g., Diebold, 1986).[2] Indeed, some shocks can cause abrupt breaks in the unconditional variance of returns and are equivalent to structural breaks in the parameters of the GARCH process governing the conditional volatility of returns. Generally those shocks invalidate statistical inference. In such a case, including dummy variables to account for such shifts diminishes the degree of persistence

[2]Kim and Nelson (1999), Mills and Wang (2003), Summers (2005), and Smith and Summers (2009) implement a Markov switching heteroskedasticity approach with two states to assess volatility in the growth rate of real GDP. The GARCH modeling approach provides an alternative to deal with this issue by assuming a constant variance process.

in conditional volatility. For example, using GARCH specifications with breaks in volatility, Fang et al. (2008) and Fang and Miller (2008) show that the time-varying variance falls sharply or disappears, once they incorporate the break in the variance equation of output. Also Balke and Fomby (1991), Atkinson et al.(1997) or Darné and Diebolt (2004), *inter alia*, show that specific events have a dramatic impact on modelling macroeconomic and financial time series. This type of event includes, for example, oil shocks, wars, financial slumps, changes of policy regimes, natural disasters, etc. Due to their unpredictable nature and large impact on macroeconomic and financial relationships, these extraordinary events are referred to as (infrequent) large shocks and are often identified as breaks or outliers. Finally, as suggested by Hamilton (2008), even if one's interest is in estimating the conditional mean, correctly modeling the conditional variance can still be quite important, for two reasons: (i) hypothesis tests about the mean in a model in which the variance is misspecified will be invalid, with a "spurious regression" possibility; and (ii) the inference about the conditional mean can be inappropriately influenced by outliers and high-variance episodes if one has not incorporated the conditional variance directly into the estimation of the mean, and infinite relative efficiency gains may be possible.

In this paper, our aim is to assess the effects of breaks on macroeconomic volatility measurement, including the Great Recession period. First, we identify breaks for both mean and variance in the GDP series of 10 advanced countries.[3] Our empirical results do not give evidence to the end of the Great Moderation period but rather that the Great Recession is characterized by a dramatic temporary effect on the output growth but not on its volatility, at least for all the countries included in the analysis. Therefore, from our analysis based on recent GDP data, there is currently no evidence of a new regime of high macroeconomic volatility. Then, in a second step, we show that neglecting those breaks can lead to spurious macroeconomic modeling and that financial and global uncertainties are likely to play a non-negligible role during the Great Recession period.

The remainder of this paper is organized as follows: Section 2 briefly describes the methodology of break detection for both GDP growth rates and its variance and presents the results. The effects of breaks on output volatility modelling are presented in Section 3. Section 4 discussed the possible link between the Great Recession and the economic uncertainty. Finally, Section 5 concludes.

[3]US, UK, Japan, Germany, France, Italy, Canada, Australia, Spain and, the Netherlands.

2 Detecting breaks

In this section, we present the methodology we implement in order to detect breaks within the GDP series, for both mean and variance, as well as the main empirical results we get. We focus on quarterly growth rates of real GDP series stemming from Quartertly National Accounts of each country, as provided by the OECD in its Economic Outlook database. All the series start in 1970Q1 and end in 2011Q4.

2.1 Detection of breaks in mean

Breaks in macroeconomic series reflect extraordinary, infrequently occurring events or shocks that have major effects on modeling macroeconomic time series. There are several methods stemming from the statistical field for detecting breaks or outliers based on the so-called *intervention analysis* approach, as originally put forward by Box and Tiao (1975). In this paper, we implement an improved detection algorithm proposed by Chen and Liu (1993), which is readily available with slight modifications by Gómez and Maravall (1997). Especially, we focus on break detection from AutoRegessive Moving-Average (ARMA) models to emphasize the large shocks that have affected the output growth. Let's assume that we observe (y_t) the quarterly growth rate of macroeconomic output which follows the following process:

$$y_t = z_t + f(t) \tag{1}$$

where

$$\phi(L)z_t = \theta(L)a_t \qquad a_t \sim N(0, \sigma_a^2), \tag{2}$$

where z_t is an ARMA(p,q) process[4] (L being the usual lag operator) and $f(t)$ contains exogenous disturbances or breaks. Following Chen and Liu (1993), we will consider three various types of breaks: additive outlier (AO), level shift (LS) and temporary change (TC). The models for different $f(t)$ are as follows:

$$\begin{aligned} \text{AO:} \quad & f_{AO}(t) = \omega_{AO} I_t(\tau_j) \\ \text{LS:} \quad & f_{LS}(t) = [1/(1-L)]\omega_{LS} I_t(\tau_j) \\ \text{TC:} \quad & f_{TC}(t) = [1/(1-\delta L)]\omega_{TC} I_t(\tau_j) \end{aligned} \tag{3}$$

[4]The orders p and q of the ARMA model are based on specification tests and information criteria.

where ω_i, for $i =$ AO, LS, TC, denotes the magnitude of the break[5], $I_t(\tau_j)$ is an indicator function that takes the value of 1 at time $t = \tau_j$ and 0 otherwise; τ_j being the unknown date at which the break occurs, with $j = 1, \ldots, m$, and m is the number of breaks. These various types of breaks differently affect the observations: AO causes an immediate and one-shot effect on the observed series; LS produces an abrupt and permanent step change in the series (permanent shock); TC produces an initial effect which dies out gradually with time (transitory shock). In this latter case, the parameter δ controls the pace of the dynamic dampening effect ($0 < \delta < 1$). Note also that the detection algorithm provides an estimated date for the break through a sequential procedure. We refer to Appendix A for more details on the break detection methodology.

Now we apply this previous methodology in order to detect outliers on GDP growth rate series for the 10 countries considered in our analysis (US, UK, Japan, Germany, France, Italy, Canada, Australia, Spain, and the Netherlands.), from 1970Q1 to 2011Q4.[6] In Table 1, all detected breaks are given by country, with their type, timing and t-statistics. In addition, we also associate the date of each break to a specific event that occurred near that date. First, we find breaks for all the output growths and many of the detected large negative breaks are associated with the Great Recession. Clearly, all the countries in the sample present a break in mean during this recent macroeconomic recession, except Australia, reflecting thus the large synchronization among advanced countries of this specific event, as shown for example by Imbs (2010). This result confirms the findings of Balke and Fomby (1994) and Darné and Diebold (2004) that severe recessions can be associated with outliers.

More specifically, a sequence of breaks appears among countries: the UK being the first country to be affected in 2008Q2, then Spain in 2008Q3 and last Canada, France, Germany, Italy, Japan, the Netherlands and the US in 2008Q4. When looking at the amplitude of breaks, Italy was strongly hit through a sequence of two consecutive breaks, as an additive outlier is also detected in 2009Q1. We note that Japan and UK are among the most affected countries, which seems consistent with economic facts. Indeed, the Japanese economy possesses an export-led growth which was strongly impacted by the collapse in global trade (see Baldwin, 2009), while the UK activity was largely supported by financial services until 2008 and was thus at the heart of the

[5]More precisely, it is considered that AOs are outliers which are related to an exogenous change in the series with no permanent effects, whereas TCs and LSs are more in the nature of structural changes. TCs represent short-lived shifts in a series with a return to previous levels whereas LSs are more the reflection of permanent shocks. In the remainder of the paper, we use the term “break” for AO, TC and LS.

[6]Source: OECD, Main Economic Indicators database.

financial turmoil.

Another great common feature visible within those results is the type of breaks. Indeed, all the countries experience a temporary change (TC break) in output growth during the Great Recession period, meaning that the economy was hit by the financial shock but recovers after few quarters. In fact, according to those results, it means that there is no definitive reduction of the output growth after the recession; otherwise a level shift break would have been preferred. This latter result shed some light on the current economic debate about the possible loss of potential growth in the wake of the Great Recession and thus does not imply any evidence that underlying growth has been durably affected by the recession, though there may be a drop in the level of output. This latter hypothesis cannot be assessed here by our approach. In addition, we get that the estimated pace of recovery was quite low in general as $\hat{\lambda}$ is close to 0.6 or 0.7, except for Canada that recovers at a higher speed ($\hat{\lambda} = 0.9$). It turns out that Canada was less damaged than other advanced countries by the Great Recession, mainly because of the structure of its economy relying on commodity exports. The Canadian economy was likely driven by the still buoyant commodity demand from emerging countries.

In addition to breaks related to the Great Recession, other breaks are detected within some countries, associated with the first and second oil shocks. The UK and the US, oil producers, experienced a positive shock in 1979Q2 and 1978Q2, respectively, and in 1973Q1 (only for the UK), whereas the negative shocks in 1974Q1 and in 1979Q3 for the UK are likely to due to economic recessions at that time. Last, we point out that the dotcom bubble of the nineties, which was largely financed by equity instead of debt, was much less detrimental to economic growth, as only UK and Spain exhibit a short-lived break during this specific period of time. Overall it turns out that the nature of recession appears to be a strong determinant of the type of break and hence of its macroeconomic impact. A balance sheet crisis, as the last Great Recession was, seems to largely and durably affect the drivers of growth.

We now look at the effect of taking breaks-in-mean into account on some basic statistics. Table 3 presents summary statistics for the output growth variables of all countries, for both original and break-in-mean-adjusted series. As regards the original variables, empirical statistics indicate that none of those series is Normally distributed. Japan and the Netherlands are slightly more volatile, as measured by standard deviation, than other countries. As regards higher moments of the distribution, France, Italy, Japan and the US exhibit evidence of significant negative skewness and all the countries display excess kurtosis. Blanchard and Simon (2001) note that the distribution of output growth exhibits excess kurtosis, if large and infrequent shocks occur. This suggests that the evidence of kurtosis may reflect extreme changes in mean and variance of growth rate, such as the Great Moderation and the Great Recession. The Ljung-Box test leads to the presence of serial correlation in the series, except for the Netherlands. The Lagrange Multiplier test for the presence of ARCH effects clearly indicates that all output growth variables, except the UK, show strong conditional heteroscedasticity.

Let's turn now to breaks-in-mean adjusted series, in order to adjust GDP growth series for breaks-in-mean, we incorporate the various types of outliers based on dummy variables that take a value of one from each point of structural break onwards and take a value of zero elsewhere. Once breaks are accounted for, measures of non-Normality in adjusted series improve, sometimes quite dramatically, reducing excess skewness and excess kurtosis. Excess skewness disappears for France, Italy and Japan, implying that the breaks are principally responsible for the asymmetries, but still remains for the UK and the US. Excess kurtosis is still significant only for three countries (Italy, the Netherlands and the US). Therefore, this supports the fact that breaks-in-mean may cause excess kurtosis in time series, as already pointed for example by Carnero et al. (2001). However, it is sticking to note that evidence of conditional heteroscedasticity is still found for all the break-adjusted series, excluding the UK.

From the comparison of basic statistics, it turns out that accounting for breaks diminishes deviation to Normality, which is an expected result. However, this does not prevent from evidence of ARCH effects at this stage. In the Technical Appendix the plots of the density, for both original and outlier-adjusted variables, are displayed. From those graphs, we clearly see a shift to the right of all distributions after break corrections, as well as a reduction in variance.

2.2 Detection of breaks-in-variance

Once breaks-in-mean have been identified, we correct the output growth series from those breaks to get breaks-in-mean corrected series (z_t), as defined in equation (1). We first test for breaks-in-variance starting from adjusted series (z_t) using the Bai and Perron (1998, 2003) approach. Following McConnell and Perez-Quiros (2000) and Stock and Watson (2003, 2005), we assume that, for each country, the GDP growth corrected from breaks-in-mean follows a linear autoregressive (AR) process such that:[7]

$$z_t = \phi_0 + \sum_{i=1}^{p} \phi_i z_{t-i} + \varepsilon_t, \tag{4}$$

where ε_t is the serially uncorrelated error term. The lag order p in the AR(p) model is selected from the Schwarz Bayesian criterion (SBC), with the maximum lags $p_{\max} = q(T/100)^{1/4}$ where $q = 4$ for quarterly data.[8]
Once parameters in equation (4) have been estimated, we test for breaks-in-variance in the absolute values of the estimated residuals, $\hat{\varepsilon}_t$, from the following equation:

$$|\hat{\varepsilon}_t| = \alpha + u_t \tag{5}$$

where u_t is the regression error term at time t.[9]

In addition to the Bai-Perron test, we also applied two other well-known break-in-variance detection procedures: the iterative cumulative sum of squares (ICSS) algorithm proposed by Sanso et al. (2004) which is a CUSUM-type test[10], and the test put forward by Sensier and van Dijk (2004).

The test procedures of Bai-Perron and ICSS are break tests in the unconditional variance, while Sensier-van Dijk use of test for the conditional variance. The estimated breaks detected by those procedures are very closed for most of the countries (see Table 10 in Appendix), giving some robustness to the empirical results. In order to define our break-in-variance dating, we retain the date that common to at least two testing procedures. We refer to Appendix B for further details on multiple detection procedures and results for breaks in variance.

[7]Peña (1990) and Chen and Liu (1993), among others, show that outliers can bias the estimation of ARMA parameters.

[8]To check for remaining residual autocorrelation, we apply the Ljung-Box test for residual serial correlation to each AR(p) model selected by SBC. If necessary the lag length p is increased until the null of no residual autocorrelation cannot be rejected at the 5% significance level.

[9]We also used the unbiased estimators of residuals, $\sqrt{\frac{\pi}{2}}|\hat{\varepsilon}_t|$, as suggested by McConnell and Pérez-Quirós (2000), and found the same number of breaks.

[10]The ICSS procedure has been used by Fang et al. (2008) for the G7 countries and Gadea et al. (2013) for the US. Gadea et al. (2013) found the same break-in-variance than our results for the US in 1984Q1. Note that Rodrigues and Rubia (2011) show that outliers can generate large size distortions in this test, and suggest to identify the variance changes from the outlier-adjusted data. Further, Inclán and Tiao (1994) advise that "*it is advisable to complement the search for variance changes with a procedure for outlier detection*".

Results for breaks in variance are presented in the first column of Table 2.[11] We find at least one break in volatility in all countries, except for France and Japan, and two breaks for Spain and the UK. Most of the breaks in volatility are associated with the well documented decline in output growth volatility in the eighties (Canada, Italy, the Netherlands and the US), characterized in the literature as the “Great Moderation” period. Spain and the UK experienced a break in volatility almost ten years later (1993Q3 and 1992Q2, respectively). It is noteworthy that in opposition to the previous results as regards break-in-mean detection, the timing of the decline in volatility is not synchronized, as also pointed out by Cecchetti et al. (2006). This observed pattern suggests that there is no clear common shock underlying those breaks in volatility.
Table 2 also displays the comparison of break dates in volatility of GDP growth stemming from our results with those of Fang et al. (2008), Cecchetti et al. (2006), Stock and Watson (2005), and Summers (2005). Break dates estimated through our approach are very much in line with those found by Cecchetti et al. (2006)[12] whereas there is more divergence with break dates estimated by others studies. Note however that the dates estimated for the US are remarkably consistent among studies. There seems to be also a consensus for Canada, excepting the Stock and Watson (2005) study. Different detection methods and different sample periods can explain those divergences: Summers (2005) uses a Markov-Switching model with high and low GDP volatility regimes for quarterly data covering the period 1966Q1–2002Q4; Stock and Watson (2005) test for changes in the variance of AR(4) innovations using the Quandt likelihood ratio on the period 1960Q1–2002Q4; Cecchetti et al. (2006) search for multiple breaks in GDP growth series based on Bai and Perron (1998, 2003) approach from 1970Q1 to 2003Q4; and Fang et al. (2008) use modified iterated cumulative sum of squares algorithm proposed by Sansó et al. (2004) to detect structural change in the variance of output growth on the period 1957Q1–2006Q3. Also the inclusion within the sample of the Great Recession period, exceptional by its amplitude and duration, is likely to shift the break dates, due to a lack of the robustness to the sample of those methods.

A salient feature of those empirical results lies in the fact that once we account for

[11] We find the same breaks in mean and in variance when the sample size ends in 2007Q4.

[12] Cecchetti et al. (2006) use the same methodology we applied, namely the Bai and Perron (1998, 2003) test, with a shorter sample size (1970Q2-2003Q4) and without searching breaks-in-mean. We tested for breaks-in-variance on the original series, i.e. without non-adjusted break-in-mean series, and found the same break dates than with the adjusted break-in-mean series, except for the second break for the UK. These results give robustness of our findings on breaks-in-variance dates.

breaks in mean in GDP time series, then no more breaks in volatility are identified during the Great Recession. This empirical result does not give evidence to the end of the Great Moderation regime, in opposition to the recent results obtained by Canarella et al. (2010)[13], but rather that the Great Recession has a dramatically temporary negative effect on the output growth but not on its volatility. This empirical result suggests that the Great Moderation with its low volatility of growth is likely to continue in the upcoming years. This result also confirms the findings of Chen (2011) that there is a very high probability of being in a low-volatility regime since 2009-2010[14], and the view of Clark (2009) that "*macroeconomic volatility will likely undergo occasional shifts between high and low levels, with low volatility the norm*." Clark (2009) attributes most of the rise in macroeconomic variability to larger shocks to oil prices and financial markets, or bad luck. In addition, Clark (2009) finds that the increase in volatility during the Great Recession is concentrated in some sectors of the economy (e.g., goods production, investment, and total inflation) whereas the Great Moderation affected all sectors.

3 Impact of breaks on output volatility modelling

In this section, we assess the impact on modeling of not taking breaks into account, for both conditional mean and conditional variance. As argued by Fernández-Villaverde and Rubio-Ramírez (2010), modelling volatility is important to understand the source of aggregate fluctuations, the evolution of the economy, and for policy analysis. Further, it is necessary to have an accurate modeling of volatility to propose structural models with mechanisms that generate it (Fernández- Villaverde and Rubio-Ramŕez, 2007, 2010; Justiniano and Primiceri, 2008). In this respect, we estimate an AR(p)-GARCH(1,1) model (Bollerslev, 1986) for the growth rate series on three datasets: (1) raw data; (2) break-in-mean adjusted data; and (3) break-in-mean and break-in-variance adjusted data. Indeed, GARCH-type models have proved useful in the measurement of output volatility in the empirical literature.

The conditional mean growth rate is supposed to follow an AR(p) process of the

[13] Canarella et al. (2010) estimate the end of the Great Moderation in 2007, using Markov regime-switching models. Note that the authors still carry some reservations about their findings.

[14] Chen (2011) employs a Markov regime-switching approach in G7 countries from data ending in 2010Q4.

form:

$$x_t = \phi_0 + \sum_{i=1}^{p} \phi_i x_{t-i} + \varepsilon_t, \tag{6}$$

where for all t, $x_t = y_t$ for raw series or $x_t = z_t$ for break-in-mean corrected series, with

$$\begin{aligned}
&\varepsilon_t = v_t \sqrt{\sigma_t^2}, \\
&\varepsilon_t \sim N(0, \sqrt{\sigma_t^2}), \qquad\qquad v_t \sim i.i.d.N(0,1), \\
&\sigma_t^2 = \omega + \alpha\varepsilon_t^2 + \beta\sigma_{t-1}^2
\end{aligned}$$

The lag order p is selected from the Schwarz Bayesian criterion (SBC) in order to capture growth dynamics and to produce uncorrelated residuals. Parameters should satisfy the following constraints $\omega > 0$, $\alpha \geq 0$ and $\beta \geq 0$ to guarantee the positivity of the conditional variance. The stationary of the process is achieved when the restriction $\alpha + \beta < 1$ is satisfied and the regularity condition of a GARCH(1,1) model is given by: $E[\varepsilon_t^4] = 3\alpha^2 + 2\alpha\beta + \beta^2 < 1$.

The sum of α and β quantifies the persistence of shocks to conditional variance, meaning that the effect of a volatility shock vanishes over time at an exponential rate. The GARCH models are short-term memory which define explicitly an intertemporal causal dependence based on a past time path. It is possible to shed light on the speed of the mean reversion process from GARCH parameters, based on the half-life concept. Half-life gives the point estimate of half-life (j) in quarters given as $(\alpha + \beta)^j = \frac{1}{2}$, so the half-life is given by $j = ln(0.5)/ln(\alpha + \beta)$, i.e. it takes for half of the expected reversion back towards $E(\sigma^2)$ to occur (Andersen and Bollerslev, 1997). When $\alpha + \beta = 1$ an Integrated GARCH (IGARCH) model is defined (Engle and Bollerslev, 1986), for which the unconditional variance is not finite, implying that the shocks to the conditional variance indefinitely persist.

Table 4 and Table 5 provide the estimation results for the AR(p)-GARCH(1,1) models. The parameters of the volatility models are estimated by maximizing the log-likelihood function from the Berndt et al. (1974) (BHHH) algorithm. For each country, the best model is given in bold face, owing to the higher value of the log-likelihood. We comment below the results for each of the three datasets.

Original data (y_t).

The conditions of stationarity and existence of the fourth moment are satisfied for almost all the countries (except for Italy, Spain and the US), showing that the effect of a volatility shock vanishes over time at an exponential rate. Canada, France and Japan exhibit a slightly higher volatility persistence, with estimates of persistence ranging from 0.840 to 0.874 and half-life of shocks to volatility ranging between 3.98 and 5.14 quarters. The IGARCH process captures the temporal pattern of volatility for the Netherlands, implying that the shocks to the conditional variance persist indefinitely. Finally, the UK is modeled by an ARCH(1) process, suggesting a low level of persistence.

Break-in-mean-adjusted data (z_t).

When breaks-in-mean are taken into account, the level of volatility persistence is slightly modified for most of the countries. Nevertheless, the value of α decreases and the value of β increases when the data are cleaned of breaks for Canada, Italy, the Netherlands and Spain, as also found by Carnero et al. (2001). Note that the GARCH model does not satisfy the regularity and non-negativity conditions from original data for Italy and Spain but these conditions are satisfied from break-in-mean-adjusted data, suggesting that outliers can bias these conditions. This finding confirms that of Ng and McAleer (2004), showing that outliers can affect the moment conditions of GARCH models. Further, the volatility of output growth for the UK is now modeled by a GARCH(1,1) with a high degree of persistence, $\alpha + \beta = 0.983$. More interesting, the (G)ARCH effect disappears for France, Japan and the US when outliers are taken into account, suggesting that a homoscedastic error process is more suitable. Further, the log-likelihood from break-adjusted data is higher than the one from the original data, showing the relevance of taking into account outliers in modeling the output growth, from a goodness-of-fit point of view.

Accounting for break-in-variance in break-in-mean adjusted data (z_t).

We now consider the break-in-mean adjusted data (z_t) and we estimate the model given by equation (6) and by the following equation for the conditional variance:

$$\sigma_t^2 = \omega + \alpha\varepsilon_t^2 + \beta\sigma_{t-1}^2 + \sum_{i=1}^{m} \omega_i d_{it} \qquad (7)$$

where m is the number of detected breaks in the variance, d_{it} is the dummy variable corresponding to the i^{th} detected break, and ω_i is the impact measure of d_{it}. We use the dates of break presented in Table 2. The parameter estimates of dummies variables are all found to be significant.[15] The negative estimate of the dummy variable (d_1) in the variance equation reflects exactly the Great Moderation for Canada, Italy, the Netherlands, Spain (d_2), the UK and the US. For all the countries, the improvement of the value of the maximum log-likelihood (LL) indicates that the GARCH(1,1) model from break-in-mean-adjusted data with structural breaks in volatility appears to be the most relevant to fit the data, showing the importance to account for breaks, both in mean and in variance, when modeling the output growth. When structural breaks are incorporated in the GARCH model, the volatility persistence substantially drops for Canada, Italy and Spain, with a level of 0.333, 0.202 and 0.623, respectively. It is well known that these shocks can bias the estimated persistence of volatility (see, e.g., Lamoureux and Lastrapes, 1990; Mikosch and Starica, 2004; Hillebrand, 2005). Moreover, the estimated half-life of shocks changes dramatically. For example, the half-life is of nearly 4 quarters for Canada from the original data whereas it is of less than 1 quarter after accounting for structural breaks in variance. That is, once breaks are accounted for, a shock is expected to have a much lower duration. Further, the estimates of GARCH parameters, α_1 and β_1, not only fall in size but also become non-significant in the specification that includes the variance dummy variable for the Netherlands and the UK, indicating no (G)ARCH effects. That is, the dummy variable replaces the GARCH effect. Moreover, the GARCH(1,1) model reduces to ARCH(1) for Canada, Italy and Spain.[16]

Empirical results presented in this section underline that once we correct for breaks in volatility, then the ARCH(1) model appropriately captures volatility of GDP growth rate for Canada, Italy, and Spain, whereas conditional homoscedasticity prevails for France, Japan, the Netherlands, the UK and the US. Thus we can conclude from those results that the GARCH evidence and high persistence property that appear in many research papers dealing with macroeconomic variables mainly reflect the Great Recession and the Great Moderation effects. Once taking breaks into account, this specific variance dynamics disappears.

[15] Note that Fang et al. (2008) find non-significant estimates of some dummy variables in the AR and GARCH models.

[16] Figures of conditional variance from the three datasets are given in the Technical Appendix for some countries.

4 Uncertainty and the Great Recession

Based on our previous empirical results that the Great Recession seems to be rather characterized by breaks defined as transitory changes in conditional mean, we aim now at identifying what could be the main factors lying behind this phenomenon. A possible determinant is the increase in global uncertainty as put forward by Baker and Bloom (2012) and Bloom (2013) who find a causal effect of uncertainty on growth. On the other hand, this relationship is challenged by other recent papers such as the one by Bachmann et al. (2013) who argue that there is a low impact of uncertainty on economic activity and that uncertainty is simply a by-product of recessions. In this section, our aim is to assess to what extent the previous break detection analysis may contribute to provide some insights on this specific topic.

In this respect, we examine if the transitory changes in the mean of GDP growth of the countries considered in our study, associated with the Great Recession, can be explained by three proxies of US uncertainty measures in macroeconomics, financial markets or economic policy.[17] In fact, we test here the international spillovers from a US uncertainty shock. The US macroeconomic uncertainty variable (USMACRO) is the uncertainty index on the state of the economy based on a real activity factor developed by Scotti (2012). For the uncertainty measure in US financial markets we employ the CBOE volatility index (USVIX), also known as the "fear index", based on trading of S&P 100 (OEX) options. The US economic policy uncertainty variable that we use is the index of economic policy uncertainty (USEPU) proposed by Baker, Bloom and Davis (2013), built on three components: (i) the frequency of newspaper references to economic policy uncertainty, (ii) the number of federal tax code provisions set to expire, and (iii) the extent of forecaster disagreement over future inflation and government purchases.[18]

To have a specific focus on the Great Recession period, the original GDP growth rates of countries are regressed only on the uncertainty variables and the estimations are restricted to the period ranging from 2005Q1 to 2011Q4:

$$x_t = \phi_0 + \theta unc_t + \varepsilon_t, \tag{8}$$

where for all t, $x_t = y_t$ for raw series or $x_t = z_t$ for break-in-mean corrected series, $unc_t = USMACRO_t$ for the macroeconomic variable, $unc_t = USVIX_t$ for the financial

[17] See also Chua et al. (2011) for a discussion on empirical measures of macroeconomic uncertainty.

[18] See Baker et al. (2013) for a detailed description of the EPU indexes. The data are available on www.policyuncertainty.com/index.html.

uncertainty variable, and $unc_t = USEPU_t$ for the economic policy variable. The results are given in Tables 6 and 7.

First we observe that the estimates of uncertainty variables are generally significant, suggesting that US uncertainty variables play a non-negligible role in explaining output growth in other advanced countries; an increase in uncertainty being reflected in a decrease in growth as all estimated parameters appear negative. Thus we show evidence of international spillovers from US uncertainty. This result is consistent with the findings of Bloom (2009), Bachmann and Mayer (2011) and Bloom et al. (2012) who find that their measures of uncertainty tend to be negatively correlated with business cycles.

In a second step, we do the same exercice but we use mean-adjusted data instead of original data. Specifically, breaks-in-mean associated with the Great Recession are taken into account. Thus it turns out that the $\bar{R}^2$ decreases, sometimes dramatically, whatever the uncertainty variable. For example, as regards the regression that explains UK GDP growth by the financial US uncertainty variable, the $\bar{R}^2$ value drops from 0.44 to 0.22. In some cases such as for Canada, France, Germany, Italy, Japan, and the US, we get that uncertainty variables are significant when models are estimated on original data, while they become non-significant as soon as break-in-mean are accounted for. This means that the transitory changes observed during the Great Recession are related, at least partly, to an increase in uncertainty.

Robustness checks

As robustness check of our results, we consider now domestic spillovers from uncertainty to economic growth for all the countries in our sample. In this respect, we use country-specific proxies of uncertainty in financial markets, economic policy and macroeconomy, when they are available. For the financial uncertainty variables we take: the AVIX based on S&P/ASX 200 index options for Australia; the MVX/VIXC based on the S&P/TSXă60 index options for Canada[19]; the VCAC index based on the CAC40 index options for France; the VDAX index based on the DAX300 index options for Germany; the VMIB index based on the MIB20 index options for Italy the VAEX index based on the AEX30 index options for the Netherlands; the VSTOXX based on the Dow Jones Euro Stoxx 50 index options for Spain;[20] the VFTSE based on the FTSE 100 index options for the UK, and the VXJ based on the Nikkei 225

[19]We concatenated series of the MVX index (from 2005Q1–2010Q3) and the VIXC index (from 2010Q4–2011Q4). The VIXC index has replaced the MVX index in October 2010.

[20]Spain has not official volatility index.

index options for Japan.[21] For the economic policy uncertainty, we use the country-specific uncertainty measure for Canada, France, Germany, Italy and Spain, and the Europe uncertainty index for the Netherlands, proposed by Baker et al. (2013). The macroeconomic uncertainty index we employ the country-specific measure for Canada, Japan and the UK, and the Euro area index for France, Germany, Italy, The Netherlands and Spain, developed by Scotti (2012).

We also employ two others US macroeconomic uncertainty variables: (1) the forecasts dispersion in the general business situation question, stemming from the Business Outlook Survey (USDISP) proposed by Bachmann et al. (2013).[22]; and (2) the macro uncertainty factor developed by Jurado et al. (2013), based on a large number of economic time series.

The results are given in Tables 8-9. On the whole, we find similar results from country-specific uncertainty variables than from US uncertainty variables: (i) all uncertainty variables are significant with a negative sign; (ii) the $\bar{R}^2$ decreases once the break-in-mean is taken into account; and (iii) the uncertainty variable becomes non-significant from the break-in-mean adjusted series.

We have also introduced the lagged GDP growth rate and uncertainty variables in the conditional mean growth, and obtained similar general results. The results are given in the Technical Appendix.

As a general result, we get from our analysis based on the comparison between original and break-in-mean-adjusted data that the increase in uncertainty is likely to be related to the Great Recession in the main advanced countries. In addition, it turns out that there are some spillovers effects stemming from the US that propagate through the uncertainty channel.

5 Conclusion

In this paper, we focus on break detection on output growth for a set of advanced countries, based on statistical test procedures. It turns out that the Great Recession period is characterized by large breaks in mean of transitory nature, while dates of breaks in variance are consistent with the Great Moderation period in the eighties. This leads us to conclude that there is no evidence towards an end of the low output volatility

[21] See Siriopoulos and Fassas (2013) for a discussion on the implied volatility indexes.

[22] A number of papers use forecast disagreement based on the Survey of Professional Forecasters as a proxy for uncertainty. However, some papers have a more critical view about using disagreement as a proxy for uncertainty (see, e.g., Boero et al., 2008, 2012; Rich and Tracy, 2010; Rich et al., 2012; Bachmann et al., 2013)

period, but rather that the Great Recession has a dramatically temporary effect on the output growth but not on its volatility. In addition, we show that accounting for those types of breaks-in-mean and in-variance modify the analysis based on GARCH-type models when one tries to evaluate macroeconomic volatility. Finally, we suggest that financial and global uncertainties are likely to play a non-negligible role during the Great Recession period.

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Table 1: Large shocks detected in the GDP growth.

Country	Date	Type	δ^a	size	t-stat	Events
Australia	1974Q2	AO		-0.032	-3.53	Oil shock
	1976Q1	AO		0.036	3.90	
Canada	2008Q4	TC	0.9	-0.015	-2.45	Great Recession
France	1974Q4	AO		-0.022	-5.15	Oil shock
	2008Q4	TC	0.6	-0.019	-4.81	Great Recession
Germany	1987Q1	AO		-0.032	-3.53	
	2008Q4	TC	0.6	-0.029	-4.15	Great Recession
Italy	2008Q4	TC	0.7	-0.037	-3.79	Great Recession
	2009Q1	AO		-0.027	-4.46	Great Recession
Japan	1974Q1	AO		-0.043	-4.54	Oil shock
	2008Q4	TC	0.7	-0.037	-3.90	Great Recession
Netherlands	1979Q1	AO		-0.055	-5.44	Oil shock
	1979Q2	AO		0.052	5.17	Oil shock
	2008Q4	TC	0.6	-0.025	-3.74	Great Recession
Spain	1990Q4	AO		0.036	6.62	
	1991Q1	AO		-0.028	-5.16	
	2008Q3	TC	0.7	-0.021	-4.44	Great Recession
UK	1973Q1	AO		0.044	6.80	Oil shock
	1974Q1	AO		-0.032	-4.99	Oil shock
	1979Q2	AO		0.036	5.59	Oil shock
	1979Q3	TC	0.7	-0.037	-6.59	Oil shock
	1990Q3	TC	0.7	-0.021	-4.15	
	2008Q2	TC	0.6	-0.032	-6.36	Great Recession
US	1978Q2	AO		0.032	4.32	Oil shock
	2008Q4	TC	0.7	-0.025	-3.92	Great Recession

Notes: [a] δ denotes the parameter which designed to model the pace of the dynamic dampening effect for the outlier TC ($0 < \delta < 1$).

Table 2: Comparison of structural breaks in volatility of GDP growth.

Country	Break date Our results	Fang et al. (2008)	Cecchetti et al. (2006)	Stock and Watson (2005)	Summers (2005)
Australia	*1985Q2*	–	1984Q3	–	1984Q3
Canada	*1987Q1*	1987Q1	1987Q2	1991Q2	1988Q1
France	–	–	–	1968Q1	1976Q3
Germany	–	–	–	–	–
Italy	*1984Q1*	1996Q1	1983Q3	1980Q1	1980Q2
Japan	–	1975Q1	–	–	1975Q2
Netherlands	*1986Q4*	–	1983Q4	–	–
	–	–	1994Q3	–	–
Spain	*1986Q1*	–	1985Q2	–	–
	1993Q3	–	1993Q2	–	–
UK	*1977Q2*	–	1981Q2	1980Q1	1982Q2
	1992Q2	1991Q1	1991Q4	–	–
US	*1984Q1*	1983Q2	1984Q2	1983Q2	1984Q4
Sample size	1970Q2 2011Q4	1957Q1 2006Q3	1970Q2 2003Q4	1960Q1 2002Q4	1966Q1 2002Q4
Methodology		CUSUM-type test	Bai-Perron test	Quandt LR	Markov-switching model

Notes:

Table 3: Descriptive Statistics and tests.

Country	Outlier	Mean (%)	St. dev.	Skewness	Excess Kurtosis	$Q(10)$	$LM(10)$
Australia	Original	0.78	0.0098	0.116	1.59*	26.4*	32.7*
	Break-adj.	0.78	0.0090	0.064	0.86*	14.4	19.8*
Canada	Original	0.72	0.0083	-0.084	0.81*	44.6*	38.1*
	Break-adj.	0.75	0.0080	0.093	0.51	36.7*	45.3*
France	Original	0.57	0.0060	-0.661*	2.16*	110.3*	23.3*
	Break-adj.	0.62	0.0052	0.063	0.10	111.1*	20.8*
Germany	Original				*	*	*
	Break-adj.				*	*	*
Italy	Original	0.49	0.0087	-0.338	3.05*	61.9*	26.8*
	Break-adj.	0.54	0.0079	0.311	1.30*	59.7*	64.8*
Japan	Original	0.66	0.0115	-0.676*	2.15*	41.7*	18.4*
	Break-adj.	0.74	0.0099	0.126	0.05	50.3*	17.1**
Netherlands	Original	0.61	0.0118	-0.097	4.80*	11.0	30.7*
	Break-adj.	0.66	0.0099	0.053	1.86*	6.1	37.3*
Spain	Original	0.68	0.0079	0.007	1.60*	133.4*	48.5*
	Break-adj.	0.72	0.0068	0.093	0.23	141.9*	29.7*
UK	Original	0.56	0.0099	0.123	4.17*	20.5*	15.6
	Break-adj.	0.65	0.0070	-0.452*	0.71	17.7**	32.3*
US	Original	0.69	0.0087	-0.334*	2.07*	39.2*	17.0**
	Break-adj.	0.72	0.0078	-0.467*	1.18*	36.8*	29.7*

Notes: * and ** mean significant at 5% and 10% level, respectively. $Q(10)$ is the Box Pierce statistics at lag 10 of the standardized residuals. It is asymptotically distributed as $\chi^2(k)$, where k is the lag length. $LM(10)$ is the ARCH LM test at lag 10. It is distributed as $\chi^2(q)$, where q is the lag length.

Table 4: Estimation results for GARCH models.

Country	Type	ϕ_0	ϕ_1	ϕ_2	ϕ_3	ϕ_4	ω	α	β	d_1	d_2	$\alpha+\beta$	half-life	LL
Australia	Original	0.785 (12.19)	−0.026 (−0.27)	−0.074 (−0.73)	0.172 (1.99)	−0.212 (−2.87)	0.851 (6.89)							-223.5
	Outlier-adjusted	0.782 (11.39)	0.043 (0.46)	−0.013 (−0.14)	0.160 (1.99)	−0.190 (−2.86)	0.749 (7.24)							-212.8
	Outlier-adj. & dummy	0.802 (12.86)	0.068 (0.84)	0.086 (1.04)	0.084 (1.15)	−0.176 (−2.89)	1.378 (5.10)		−0.961 (−3.41)					**-199.8**
Canada	Original	0.718 (8.77)	0.479 (6.35)				0.091 (2.79)	0.391 (3.07)	0.450 (4.19)			0.840	3.98	-170.7
	Outlier-adjusted	0.748 (9.61)	0.391 (4.83)				0.091 (2.36)	0.342 (2.30)	0.504 (3.77)			0.846	4.14	-169.1
	Outlier-adj. & dummy	0.719 (8.84)	0.434 (5.62)				0.615 (4.14)	0.333 (2.18)	–	−0.414 (−2.80)		0.333	0.63	**-166.3**
France	Original	0.535 (5.45)	0.311 (3.90)	0.412 (4.13)	0.040 (0.39)	−0.220 (−2.51)	0.030 (0.95)	0.156 (1.66)	0.717 (4.05)			0.874	5.15	-104.2
	Outlier-adjusted	0.593 (7.53)	0.322 (4.40)	0.354 (4.58)	0.090 (0.99)	−0.187 (−2.02)	0.175 (6.52)	–	–			–	–	**-91.2**
Germany	Original	0.512 (4.46)	0.025 (0.28)	0.063 (0.79)	0.078 (1.05)	0.175 (2.06)	0.539 (4.20)	0.407 (1.66)	–			0.407	–	-215.6
	Outlier-adjusted	0.541 (4.33)	0.054 (0.70)	0.086 (1.09)	0.155 (2.19)	0.152 (1.92)	0.331 (2.02)	0.143 (1.78)	0.397 (1.71)			0.539	–	**-206.31**
Italy	Original[a]	0.486 (6.70)	0.440 (4.18)	−0.086 (−1.07)	0.226 (2.72)	−0.170 (−2.63)	0.255 (4.55)	0.634 (2.64)	–			–	–	–
	Outlier-adjusted	0.507 (7.24)	0.456 (4.18)	−0.107 (−1.02)	0.204 (1.92)	−0.164 (−2.03)	0.271 (3.96)	0.499 (1.75)	–			0.309	0.59	-166.0
	Outlier-adj. & dummy	0.482 (6.56)	0.381 (4.77)	−0.047 (−0.63)	0.232 (3.52)	−0.196 (−3.11)	0.712 (4.36)	0.254 (1.87)	–	−0.518 (−3.20)		0.202	0.43	**-156.1**

Notes: $\alpha+\beta$ measures the volatility persistence. Half-life gives the point estimate of half-life (j) in days given as $(\alpha+\beta)^j = \frac{1}{2}$. [a] denotes that the condition for existence of the fourth moment of the GARCH is not observed. [b] denotes that an IGARCH model has been estimated because the GARCH constraints were not satisfied.

Table 5: Estimation results for GARCH models.

Country	Type	ϕ_0	ϕ_1	ϕ_2	ϕ_3	ϕ_4	ω	α	β	d_1	d_2	$\alpha+\beta$	half-life	LL
Japan	Original	0.684 (3.93)	0.121 (1.48)	0.128 (1.56)	0.321 (3.33)		0.196 (2.02)	0.235 (1.94)	0.610 (5.23)			0.874	5.15	-237.9
	Outlier-adjusted	0.721 (5.14)	0.133 (1.61)	0.074 (0.90)	0.282 (3.80)		0.830 (8.79)	–	–			–	–	**-221.4**
	Outlier-adj. & dummy	1.153 (9.57)	0.010 (0.12)	−0.039 (−0.46)	0.168 (2.20)		0.766 (8.35)	–	–			–	–	**-214.7**
Netherlands	Original[b]	0.597 (5.49)	0.075 (0.75)	0.174 (2.36)	0.160 (1.96)		0.010 (1.16)	0.129 (3.41)	0.871 (−−)			1.000	–	-229.9
	Outlier-adjusted	0.644 (7.58)	0.049 (0.53)	0.075 (0.87)	0.156 (1.85)		0.011 (1.06)	0.097 (2.24)	0.888 (21.6)			0.984	43.0	-207.8
	Outlier-adj. & dummy	0.658 (11.7)					1.932 (5.78)	–	–	−1.58 (−4.64)		–	–	**-206.7**
Spain	Original[a]	0.678 (5.13)	0.425 (3.91)	0.434 (4.52)	0.155 (1.59)	−0.231 (−2.62)	0.022 (1.97)	0.303 (2.36)	0.649 (5.90)			–	–	–
	Outlier-adjusted	0.688 (4.81)	0.354 (3.31)	0.339 (3.71)	0.249 (2.68)	−0.180 (−1.99)	0.015 (1.39)	0.185 (1.98)	0.768 (7.44)			0.954	14.7	-118.6
	Outlier-adj. & dummy	0.857 (5.56)	0.543 (5.33)	0.151 (1.64)	0.159 (2.54)		0.120 (2.57)	0.623 (2.26)	–	0.660 (2.98)	−0.720 (−3.31)	0.623	1.46	**-113.2**
UK	Original	0.586 (4.40)	0.427 (2.00)				0.476 (4.28)	0.533 (2.09)	–			0.533	1.10	-210.9
	Outlier-adjusted	0.702 (10.9)	0.294 (3.28)				0.007 (1.17)	0.099 (2.37)	0.884 (23.6)			0.983	40.4	-156.8
	Outlier-adj. & dummy	0.673 (11.6)	0.268 (3.52)				1.159 (4.34)	–	–	−0.681 (−2.43)	−0.289 (−3.13)	–	–	**-151.0**
US	Original[a]	0.801 (7.86)	0.287 (2.96)	0.243 (2.86)			0.031 (1.58)	0.237 (2.04)	0.732 (7.78)			–	–	–
	Outlier-adjusted	0.726 (7.32)	0.245 (2.58)	0.177 (1.71)			0.535 (6.87)	–	–			–	–	-184.8
	Outlier-adj. & dummy	0.729 (8.36)	0.229 (3.05)	0.271 (3.41)			1.179 (5.63)	–	–	−0.953 (−4.51)		–	–	**-158.3**

Notes: $\alpha+\beta$ measures the volatility persistence. Half-life gives the point estimate of half-life (j) in days given as $(\alpha+\beta)^j = \frac{1}{2}$. [a] denotes that the condition for existence of the fourth moment of the GARCH is not observed. [b] denotes that an IGARCH model has been estimated because the GARCH constraints were not satisfied.

Table 6: Regression of US uncertainty variables on GDP growth (2005Q1-2011Q4).

Country	Type	ϕ_0	USVIX	USEPU	USMACRO	$\overline{R}^2$
Australia	Original	1.192 (5.74)	−0.024 (−2.79)			0.20
		1.109 (3.94)		−0.004 (−1.67)		0.06
		1.311 (4.59)			−0.577 (−2.37)	0.15
Canada	Original[a]	1.393 (5.56)	−0.046 (−3.79)			0.42
	[a]	1.618 (4.55)			−1.103 (−3.65)	0.31
	Outlier-adj.	0.931 (3.92)	−0.017* (−1.70)			0.07
		0.897 (2.75)			−0.300* (−1.07)	0.01
France	Original	1.181 (6.82)	−0.044 (−6.12)			0.58
		0.916 (2.78)		−0.006 (−2.22)		0.13
		1.310 (4.66)			−0.977 (−4.08)	0.37
	Outlier-adj.	0.608 (3.30)	−0.008* (−0.99)			0.00
		0.622 (2.54)		−0.001* (−0.73)		0.00
		0.410 (1.64)			0.030 (0.14)	0.00
Germany	Original	1.996 (5.19)	−0.073 (−4.62)			0.43
		1.570 (2.44)		−0.010 (−1.91)		0.09
		2.421 (4.42)			−1.825 (−3.92)	0.35
	Outlier-adj.	1.111 (2.93)	−0.018* (−1.12)			0.01
		1.116 (2.22)		−0.003* (−0.76)		0.00
		1.038 (2.03)			−0.280* (−0.64)	0.00
Italy	Original[a]	1.433 (6.84)	−0.066 (−6.24)			0.54
		1.139 (2.27)		−0.010 (−2.43)		0.16
		1.622 (3.65)			−1.464 (−3.87)	0.34
	Outlier-adj.	0.562 (2.36)	−0.012* (−1.27)			0.02
		0.601 (1.88)		−0.003* (−1.02)		0.01
		0.278* (0.85)			−0.009* (−0.03)	0.00

Notes: USVIX denotes the US financial uncertainty variable based on VIX index; USEPU denotes the US economic policy uncertainty variable proposed by Baker et al. (2012). USMACRO denotes the US macroeconomic uncertainty variable proposed by Scotti (2012).

Table 7: Regression of US uncertainty variables on GDP growth (2005Q1-2011Q4).

Country	Type	ϕ_0	USVIX	USEPU	USMACRO	$\overline{R}^2$
Japan	Original[a]	1.620 (3.30)	−0.069 (−2.74)			0.25
		2.302 (3.35)			−1.974 (−3.37)	0.28
	Outlier-adj.	0.165 (0.68*)	0.011* (0.51)			0.00
		0.110 (0.21*)			0.269* (0.59)	0.00
Netherlands	Original[a]	1.655 (8.93)	−0.060 (−7.02)			0.55
		1.742 (4.21)		−0.012 (−3.61)		0.32
		1.924 (4.50)			−1.406 (−3.91)	0.36
	Outlier-adj.[a]	0.867 (3.32)	−0.011* (−0.94)			0.00
		1.338 (3.90)		−0.006 (−2.14)		0.12
		1.726 (4.11)			−1.252 (−3.51)	0.29
Spain	Original[a]	1.562 (8.18)	−0.059 (−7.70)			0.72
	[a]	1.677 (5.17)		−0.012 (−3.30)		0.48
		1.569 (4.55)			−1.170 (−3.99)	0.36
	Outlier-adj.[a]	1.137 (6.70)	−0.028 (−4.05)			0.36
		1.466 (7.49)		−0.008 (−5.24)		0.50
		0.833 (2.97)			−0.285* (−1.19)	0.02
UK	Original	1.464 (4.78)	−0.059 (−4.67)			0.44
		1.293 (2.59)		−0.009 (−2.40)		0.15
		1.669 (3.65)			−1.345 (−3.46)	0.29
	Outlier-adj.	1.152 (5.03)	−0.027 (−2.91)			0.22
		1.362 (4.45)		−0.007 (−2.78)		0.21
		1.171 (3.59)			−0.558 (−2.01)	0.10
US	Original	1.552 (6.64)	−0.057 (−5.97)			0.56
		1.025 (2.42)		−0.006 (−1.85)		0.08
		2.003 (6.23)			−1.539 (−5.62)	0.53
	Outlier-adj.	0.783 (3.20)	−0.009* (−0.90)			0.00
		0.633 (2.04)		−0.001* (−0.17)		0.00
		0.801 (2.45)			−0.195* (−0.70)	0.00

Notes: USVIX denotes the US financial uncertainty variable based on VIX index; USEPU denotes the US economic policy uncertainty variable proposed by Baker et al. (2012). USMACRO denotes the US macroeconomic uncertainty variable proposed by Scotti (2012).

Table 8: Regression of US and country-specific uncertainty variables on GDP growth (2005Q1-2011Q4).

Country	Type	ϕ_0	VIX	EPU	USFAC	USDISP	$\bar{R}^2$
Australia	Original	−− (−−)	−− (−−)				–
		0.821 (7.02)			−0.147 (−2.16)		0.12
Canada	Original[a]	1.457 (7.37)	−0.053 (−5.60)				0.49
		0.764 (6.00)			−0.361 (−4.88)		0.46
		6.092 (3.95)				−8.140 (−3.71)	0.32
	Outlier-adj.[a]	0.967 (4.83)	−0.020 (−2.51)				0.09
		0.727 (5.88)			−0.156 (−2.17)		0.12
		4.602 (3.78)				−5.763 (−3.32)	0.27
France	Original	1.108 (4.77)	−0.037 (−4.13)				0.37
		0.813 (2.69)		−0.005 (−2.08)			0.11
	[a]	0.583 (8.61)			−0.348 (−6.82)		0.64
	[a]	4.687 (2.17)				−6.373 (−1.97)	0.29
	Outlier-adj.	0.540 (2.61)	−0.004* (−0.51)				0.00
		0.321* (1.43)		0.001* (0.58)			0.00
	[a]	0.538 (7.82)			−0.092* (−1.55)		0.06
		2.826 (2.87)				−3.403 (−2.43)	0.15
Germany	Original	2.051 (3.81)	−0.069 (−3.29)				0.27
		2.010 (2.99)		−0.014 (−2.53)			0.17
		0.982 (5.37)			−0.573 (−4.15)		0.46
	[a]	8.083 (1.73)				−10.98 (−1.69)	0.22
	Outlier-adj.	0.941 (1.97)	−0.009* (−0.48)				0.00
		1.038 (1.86)		−0.003* (−0.59)			0.00
	[a]	0.913 (5.20)			−0.180* (−1.64)		0.05
		5.207 (2.51)				−6.400 (−2.17)	0.12
Italy	Original	1.550 (4.53)	−0.063 (−4.91)				0.46
	[a]	0.501 (3.84)			−0.492 (−5.08)		0.53
	Outlier-adj.	0.588 (2.17)	−0.012* (−1.20)				0.02
		0.388 (3.04)			−0.010* (−1.30)		0.03

Notes: VIX denotes the financial country-specific uncertainty variable based on VIX-type index, i.e. VIXC, VCAC, VDAX, VSTOXX, VXJ, VAEX, VSTOXX and VFTSE for Canada, France, Germany, Italy, Japan, the Netherlands, Spain and the UK, respectively; EPU denotes the economic policy country-specific uncertainty variable proposed by Baker et al. (2012). USFAC denotes the US macroeconomic uncertainty variable proposed by Jurado et al. (2013); USDISP is the US macroeconomic uncertainty variable based on forecasts dispersion proposed by Bachmann et al. (2013).

Table 9: Regression of US and country-specific uncertainty variables on GDP growth (2005Q1-2011Q4).

Country	Type	ϕ_0	VIX	EPU	USFAC	USDISP	$\overline{R}^2$
Japan	Original[a]	2.204 (4.00)	−0.079 (−4.11)				0.37
	[a]	0.674 (3.04)			−0.550 (−3.06)		0.29
	Outlier-adj.	0.294* (0.64)	0.004* (0.27)				0.00
		0.419 (1.93)			−0.010* (−0.08)		0.00
Netherlands	Original	1.706 (5.47)	−0.058 (−4.77)				0.45
		1.955 (4.73)		−0.015 (−4.13)			0.37
		0.768 (5.17)			−0.420 (−4.88)		0.46
		4.285 (2.06)				−5.641 (−1.90)	0.09
	Outlier-adj.[a]	0.772 (2.47)	−0.006* (−0.48)				0.00
		1.226 (3.30)		−0.005 (−1.69)			0.06
		0.706 (4.73)			−0.070* (−0.81)		0.00
		1.724* (1.06)				−1.557* (−0.68)	0.00
Spain	Original[a]	1.761 (9.53)	−0.060 (−8.29)				0.71
		2.092 (8.21)		−0.019 (−7.53)			0.67
		0.736 (8.42)			−0.454 (−8.94)		0.75
	Outlier-adj.[a]	1.297 (5.96)	−0.032 (−3.39)				0.43
		1.536 (7.21)		−0.011 (−5.03)			0.47
		0.6731 (6.45)			−0.152 (−2.50)		0.16
UK	Original	1.601 (4.85)	−0.067 (−4.71)				0.44
		0.936 (2.88)		−0.006 (−1.78)			0.13
		0.718 (5.39)			−0.528 (−6.83)		0.63
		5.588 (2.59)				−7.732 (−2.51)	0.16
	Outlier-adj.	1.205 (4.81)	−0.031 (−2.84)				0.21
	[a]	1.046 (4.66)		−0.004 (−1.84)			0.14
		0.681 (5.05)			−0.126* (−1.61)		0.06
		2.112* (1.41)				−2.230* (−1.04)	0.00
US	Original	0.760 (6.48)			−0.454 (−6.66)		0.62
	[a]	6.974 (2.50)				−9.540 (−2.32)	0.37
	Outlier-adj.	0.700 (5.48)			−0.112* (−1.51)		0.05
		4.467 (3.66)				−5.544 (−3.19)	0.25

Notes: VIX denotes the financial country-specific uncertainty variable based on VIX-type index, i.e. VIXC, VCAC, VDAX, VSTOXX, VXJ, VAEX, VSTOXX and VFTSE for Canada, France, Germany, Italy, Japan, the Netherlands, Spain and the UK, respectively; EPU denotes the economic policy country-specific uncertainty variable proposed by Baker et al. (2012). USFAC denotes the US macroeconomic uncertainty variable proposed by Jurado et al. (2013); USDISP is the US macroeconomic uncertainty variable based on forecasts dispersion proposed by Bachmann et al. (2013).

Appendix A: Break detection procedure

Chen and Liu (1993) and Gómez and Maravall (1997) suggest the following procedure: An ARMA model is fitted to y_t in equation (2) and the residuals are obtained:

$$\hat{a}_t = \pi(B) z_t \tag{9}$$

where $\pi(B) = \alpha(B)\phi(B)/\theta(B) = 1 - \pi_1 B - \pi_2 B^2 - \dots$.

For the three types of breaks in (1), the equation (9) becomes:

$$\begin{aligned}
\text{AO:} \quad & \hat{a}_t = a_t + \omega_{AO}\pi(B) I_t(\tau) \\
\text{LS:} \quad & \hat{a}_t = a_t + \omega_{LS}[\pi(B)/(1-B)] I_t(\tau) \\
\text{TC:} \quad & \hat{a}_t = a_t + \omega_{TC}[\pi(B)/(1-\delta B)] I_t(\tau)
\end{aligned}$$

These expressions can be viewed as a regression model for $\hat{a}_t$, i.e.,

$$\hat{a}_t = \omega_i x_{i,t} + a_t \qquad i = \text{AO, LS, TC},$$

with $x_{i,t} = 0$ for all i and $t < \tau$, $x_{i,t} = 1$ for all i and $t = \tau$, and for $t > \tau$ and $k \geq 1$, $x_{AO,t+k} = -\pi_k$ (AO), $x_{LS,t+k} = 1 - \sum_{j=1}^{k} \pi_j$ (LS), and $x_{TC,t+k} = \delta^k - \sum_{j=1}^{k-1} \delta^{k-j}\pi_j - \pi_k$ (TC), with $k = 1, \dots, T - \tau$.

The detection of the outliers is based on likelihood ratio [LR] statistics, given by:

$$\begin{aligned}
\text{AO:} \quad & \hat{\tau}_{AO}(\tau) = [\hat{\omega}_{AO}(\tau)/\hat{\sigma}_a] / \Big(\sum_{t=\tau}^{n} x_{AO,t}^2\Big)^{1/2} \\
\text{LS:} \quad & \hat{\tau}_{LS}(\tau) = [\hat{\omega}_{LS}(\tau)/\hat{\sigma}_a] / \Big(\sum_{t=\tau}^{n} x_{LS,t}^2\Big)^{1/2} \\
\text{TC:} \quad & \hat{\tau}_{TC}(\tau) = [\hat{\omega}_{TC}(\tau)/\hat{\sigma}_a] / \Big(\sum_{t=\tau}^{n} x_{TC,t}^2\Big)^{1/2} \\
\text{with} \quad & \hat{\omega}_i(\tau) = \sum_{t=\tau}^{n} \hat{a}_t x_{i,t} \Big/ \sum_{t=\tau}^{n} x_{i,t}^2 \qquad \text{for } i = \text{AO, LS, TC}, \\
\text{and} \quad & \hat{\omega}_{IO}(\tau) = \hat{a}_\tau
\end{aligned}$$

where $\hat{\omega}_i(\tau)$ ($i =$ AO, LS, TC) denotes the estimation of the break impact at time $t = \tau$, and $\hat{\sigma}_a$ is an estimate of the variance of the residual process.[23]

Breaks are identified by running a sequential detection procedure, consisting of outer and inner iterations. In the outer iteration, assuming that there are no breaks, an

[23] Due to the nature of financial data, a potential source of misspecification is (conditional) heteroscedasticity, which may inflate standard errors of estimators. Therefore, we use heteroscedasticity-consistent covariance matrices proposed by Newey and West (1987, 1994).

initial ARMA(p,q) model is estimated and the residuals ($\hat{a}_t$) are obtained. The results from the outer iteration are then used in the inner iteration to identify breaks. The LR test statistics for the four types of outliers are calculated for each observation. The largest absolute value of these test statistics:

$$\hat{\tau}_{max} = max|\hat{\tau}_i(\tau)| \qquad i = \text{AO, LS, TC and } \tau = 1,\ldots,T$$

is compared with a critical value, and if the test statistic is larger, a break is found at time $t = \tau_1$ and its type is selected (i^*). When a break is detected, the effect of this break is removed from the data as follows: the observation z_t is adjusted at time $t = \tau_1$ to obtain the corrected y_t via (1) using the estimated magnitude $\hat{\omega}_{i^*}$ and the appropriate structure of break $f(t)_{i^*}$ as in (3), i.e.

$$y_t = z_t - f(t)_{i^*}$$

We also compare the second largest absolute value of the LR statistics for the three types of breaks to the critical value, i.e. $\hat{\tau}_{max} = max|\hat{\tau}_i(\tau)|$ with $\tau \neq \tau_1$, and so on. This process is repeated until no more breaks can be found. Next, we return to the outer iteration in which another ARMA(p,q) model is re-estimated from the break-corrected data, and start the inner iteration again. This procedure is repeated until no break is found. Finally, a multiple regression is performed on the various detected breaks to identify (possible) spurious breaks.

Appendix B: Multiple break detection procedures

Appendix B1: Bai and Perron (1998, 2003) procedure

Bai and Perron (1998, 2003) propose several tests for multiple breaks. We adopt one procedure and sequentially test the hypothesis of m breaks versus $m+1$ breaks using $\sup F(m+1|m)$ statistics, which detects the presence of $m+1$ breaks conditional on finding m breaks and the supremum comes from all possible partitions of the data for the number of breaks tested. In the application of the test, we search for up to five breaks. If we reject the null of no break at the 5% significance level, we, then, estimate the break date using least squares, to divide the sample into two subsamples according to the estimated break date, and to perform a test of parameter constancy for both subsamples. We repeat this process by sequentially increasing m until we fail to reject the hypothesis of no additional structural change. In the process, rejecting m breaks favors a model with $m+1$ breaks, if the overall minimal value of the sum of squared residuals over all the segments, including an additional break, falls sufficiently below the sum of squared residuals from the model with m breaks. The break dates selected include the ones associated with this overall minimum.

According to Bai and Perron (2003) in the presence of multiple breaks there are cases when configurations of changes are such that it is very difficult to reject the null hypothesis of 0 versus 1 break in the model, but is not difficult to reject the hypothesis of 0 versus a higher number of breaks. The sequential procedure breaks down in such cases. To account for this possibility, following Bai and Perron's (2003) recommendation, in the cases when the sequential procedure suggests no breaks we consider the results of UDmax and WDmax tests. If these tests indicate the presence of at least one break, the results of the $\sup F(1|0)$ test are ignored and the number of breaks is selected upon the results of the $\sup F(2|1)$ and $\sup F(3|2)$ tests.

Appendix B2: Sanso et al. (2004) procedure

Sansó et al. (2004) propose a CUSUM-type test based on the iterative cumulative sum of squares (ICSS) algorithm developed by Inclán and Tiao (1994). This algorithm allows for detecting multiple breakpoints in variance.
Let $e_{i,t} = 100 \times \log(P_{i,t}/P_{i,t-1})$, where $P_{i,t}$ is the price of the index i at the time t, so that e_t is the percent return of the index i from period $t-1$ to t. $\{e_t\}$ is then assumed to be a series of independent observations from a normal distribution with zero mean and unconditional variance σ_t^2 for $t = 1, \dots, T$. Assume that the variance within each interval is denoted by σ_j^2, $j = 0, 1, \dots, N_T$, where N_T is the total number of variance changes and $1 < \kappa_1 < \kappa_2 < \cdots < \kappa_{N_T} < T$ are the set of breakpoints. Then the variances over the N_T intervals are defined as

$$\sigma_t^2 = \begin{cases} \sigma_0^2, & 1 < t < \kappa_1 \\ \sigma_1^2, & \kappa_1 < t < \kappa_2 \\ \dots & \\ \sigma_{N_T}^2, & \kappa_{N_T} < t < T \end{cases}$$

The cumulative sum of squares is used to estimate the number of variance changes and to detect the point in time of each variance shift. The cumulative sum of the squared observations from the beginning of the series to the kth point in time is expressed as $C_k = \sum_{t=1}^{k} e_t^2$ for $k = 1, \dots, T$. In order to test the null hypothesis of constant unconditional variance, the Inclán–Tiao statistic is given by:

$$IT = \sup_k |(T/2)^{0.5} D_k| \tag{10}$$

where $D_k = \left(\frac{C_k}{C_T}\right) - \left(\frac{k}{T}\right)$, with C_T is the sum of the squared residuals from the whole sample period. The value of k that maximizes $|(T/2)^{0.5} D_k|$ is the estimate of the break date. The ICSS algorithm systematically looks for breakpoints along the sample. If there are no variance shifts over the whole sample period, D_k will oscillate around zero. Otherwise, if there are one or more variance shifts, D_k will departure from zero. The asymptotic distribution of IT is given by $sup_r|W^*(r)|$, where $W^*(r) = W(r) - rW(1)$ is a Brownian bridge and $W(r)$ is standard Brownian motion. Finite-sample critical values can be generated by simulation.

The IT statistic is designed for i.i.d. processes, which is a very strong assumption for financial data, in which there is evidence of conditional heteroskedasticity. Sansó et al. (2004) showed that the size distortions are important for heteroskedastic conditional variance processes from Monte carlo simulations. Their results thus invalidate in practice the use of this test for financial time series. To overcome this problem, Sansó et al. (2004) proposed a new test that explicitly consider the fourth moment properties of the disturbances and the conditional heteroskedasticity. They suggested a non-parametric adjustment to the IT statistic that allows e_t to obey a wide class of dependent processes under the null hypothesis. As suggested by Sansó et al. (2004), we use a non-parametric adjustment based on the Bartlett kernel, and the adjusted statistic is given by:

$$AIT = \sup_k |T^{-0.5} G_k| \tag{11}$$

where $G_k = \hat{\lambda}^{-0.5}\left[C_k - \left(\frac{k}{T}\right)C_T\right]$, $\hat{\lambda} = \hat{\gamma}_0 + 2\sum_{l=1}^{m}\left[1 - l(m+1)^{-1}\right]\hat{\gamma}_l$, $\hat{\gamma}_l = T^{-1}\sum_{t=l+1}^{T}(e_t^2 - \hat{\sigma}^2)(e_{t-l}^2 - \hat{\sigma}^2)$, $\hat{\sigma}^2 = T^{-1}C_T$, and the lag truncation parameter m is selected using the procedure in Newey and West (1994). Under general conditions, the asymptotic distribution of AIT is also given by $sup_r|W^*(r)|$, and finite-sample critical values can be generated by simulation.

Appendix B3: Sensier and van Dijk (2004) procedure

The Sensier and van Dijk (2004) procedure is based on the residuals of equation (4) where ε_t is supposed to be a martingale difference sequence with time-varying conditional σ_t^2 such as :

$$\sigma_t = \sigma_1\{1 - I(t > \tau_m)\} + \sigma_2 I(t > \tau_m), \tag{12}$$

where τ_m is the date of break and $I(.)$ is the indicator function. The test for a structural change in the conditional standard deviation is based on the absolute value of estimated residuals $\hat{\varepsilon}_t$ supposed to follow the following regression:

$$\sqrt{\frac{\pi}{2}}\,|\hat{\varepsilon}_t| = \delta_1 \{1 - I(t > \tau_m)\} + \delta_2 I(t > \tau_m) + u_t, \tag{13}$$

where u_t is a white noise process. The break date τ_m is unknown and the likelihood-ratio-based test is used in the version of the test we implement. We require both pre- and postbreak periods to contain at least 5% of the available observations. We implement the method of Hansen (1997) based on bootstrap in order to obtain approximate p-values.

Table 10: Structural breaks in volatility of GDP growth.

	Break date			
Country	Bai-Perron	ICSS	Sensier-vanDijk	Selected date
Australia	1985Q2	1984Q1	1985Q2	1985Q2
Canada	1987Q1	1990Q4	1991Q2	
France	–	–	–	–
Germany	–	–	–	–
Italy	1984Q1	1979Q4	1984Q1	1984Q1
Japan	–	–	1987Q1	–
Netherlands	1986Q4	1986Q4	1987Q3	1986Q4
Spain	1984Q4	1986Q1	1986Q1	1986Q1
	1993Q3	1993Q2	1995Q3	1993Q3
UK	1977Q2	1977Q2	1977Q2	1977Q2
	1992Q2	1992Q2	1992Q2	1992Q2
US	1984Q1	1984Q2	1984Q1	1984Q1

Notes: we retain the date that common to at least two testing procedures as our break-in-variance dating.

Does the Great Recession imply the end of the Great Moderation? International evidence

Technical Appendix

Amélie CHARLES[*]
Audencia Nantes, School of Management

Olivier DARNÉ[†]
LEMNA, University of Nantes

Laurent FERRARA[‡]
Banque de France and
EconomiX, University Paris Ouest La Défense

[*]Audencia Nantes, School of Management, 8 route de la Jonelière, 44312 Nantes Cedex 3. Email: acharles@audencia.com.

[†]Corresponding author: LEMNA, University of Nantes, IEMN–IAE, Chemin de la Censive du Tertre, BP 52231, 44322 Nantes, France. Email: olivier.darne@univ-nantes.fr.

[‡]EconomiX, University Paris Ouest La Défense, and Banque de France, International Macroeconomics Division. Email: laurent.ferrara@banque-france.fr.

Regressions with lagged GDP growth rate and uncertainty variables

We also introduced the uncertainty variables in the conditional mean growth rate as follow:

$$x_t = \phi_0 + \sum_{i=1}^{4} \phi_i x_{t-i} + \sum_{j=0}^{2} \theta_j unc_{t-j} + \varepsilon_t, \tag{1}$$

where for all t, $x_t = y_t$ for raw series or $x_t = z_t$ for break-in-mean corrected series, $unc_t = USDISP_t$ for the macroeconomic variable, $unc_t = USVIX_t$ for the financial uncertainty variable, and $unc_t = USEPU_t$ for the economic policy variable. When a variable is significant in t and $t-1$ with opposed signs, we integrate it in first difference, or in second difference if it is necessary. The results are given in Tables 1 and 3.

Table 1: Regression of US uncertainty variables on GDP growth (2005Q1-2011Q4).

Country	Type	ϕ_0	ϕ_1	ϕ_2	ϕ_3	USVIX	DUSVIX(-1)	D2USVIX	USEPU(-1)	D2USEPU	USDISP	USDISP(-1)	$\overline{R}^2$
Australia	Original	1.192 (5.74)	–	–	–	−0.024 (−2.79)							0.20
		1.841 (4.92)	–	–	−0.547 (−2.82)				−0.007 (−2.91)				0.28
Canada	Original	0.172 (1.58)	0.609 (4.71)	–	–		−0.045 (−3.94)						0.58
		4.693 (3.30)	0.458 (3.18)	–	–						−6.388 (−3.20)		0.50
	Outlier-adj.	0.315 (2.55)	0.484 (3.12)	–	–		−0.039 (−3.80)						0.42
		4.602 (3.78)	–	–	–						−5.763 (−3.32)		0.27
France	Original	0.104 (1.26)	0.345 (2.26)	0.361 (2.30)	–			−0.032 (−4.64)					0.62
		0.177 (1.54)	0.499 (3.09)	–	–					−0.009 (−2.12)			0.39
		4.729 (4.00)	–	0.435 (2.96)	–						−6.560 (−3.90)		0.46
	Outlier-adj.	0.477 (6.03)	–	–	–			−0.015 (−2.16)					0.13
		0.508 (5.64)	–	–	–					−0.006 (−1.74)			0.08
		2.942 (2.92)	–	–	–						−3.540 (−2.48)		0.17
Germany	Original	1.765 (5.51)	–	–	–	−0.058 (−4.43)	−0.071 (−4.34)						0.70
		0.401 (1.93)	0.491 (3.15)	–	–					−0.022 (−2.92)			0.40
		7.407 (3.16)	0.436 (2.87)	–	–						−10.24 (−3.08)		0.40
	Outlier-adj.	0.815 (7.04)	–	–	–		−0.077 (−5.67)						0.56
		0.897 (5.13)	–	–	–					−0.014 (−2.09)			0.12
		5.417 (2.63)	–	–	–						−6.645 (−2.27)		0.14
Italy	Original	1.173 (4.66)	–	–	–	−0.052 (−5.06)	−0.050 (−3.89)						0.71
		0.127 (0.84)	0.491 (3.29)	–	–					−0.018 (−3.16)			0.44
		7.406 (3.42)	–	–	–							−10.54 (−3.43)	0.29
	Outlier-adj.	0.141 (1.16)	0.409 (2.08)	–	–								0.12
		0.141 (1.16)	0.409 (2.08)	–	–								0.12
		3.082 (2.16)	–	–	–							−3.964 (−1.96)	0.10

Notes: USVIX denotes the US financial uncertainty variable; DUSVIX(-1) is the first difference of USVIX variable with one lag; D2USVIX is the second difference of the USVIX variable. USEPU(-1) denotes the US economic policy uncertainty variable, with one lag; D2USEPU is the second difference of the USEPU variable. USDISP denotes the US macroeconomic uncertainty variable; USDISP(-1) is the one-lagged USDISP variable.

Table 2: Regression of US uncertainty variables on GDP growth (2005Q1-2011Q4).

Country	Type	ϕ_0	ϕ_1	ϕ_2	ϕ_3	USVIX	USVIX(-1)	DUSVIX	DUSVIX(-1)	USEPU	DUSEPU	DUSEPU(-1)	USDISP	DUSDISP(-1)	$\bar{R}^2$
Japan	Original	0.121 (0.52)	–	–	–				−0.094 (−3.42)						0.30
	Outlier-adj.	0.497 (1.93)	–	–											
Netherlands	Original	1.967 (8.34)	–	–	–	−0.035 (−2.81)	−0.039 (−3.19)								0.68
		0.187 (1.40)	0.609 (4.39)	–	–							−0.018 (−3.12)			0.53
		0.070 (0.56)	0.683 (4.97)	–	–									−6.958 (−3.26)	0.55
	Outlier-adj.	1.176 (4.51)	–	–	–		−0.025 (−2.26)								0.14
		0.700 (5.63)	–	–	–						−0.012 (−2.02)				0.11
		0.409 (2.62)	0.345 (1.99)	–	–									−7.229 (−3.87)	0.37
Spain	Original	0.006 (0.10)	0.887 (12.4)	–	–				−0.024 (−3.89)						0.87
		0.536 (2.17)	0.994 (7.63)	–	−0.323 (−2.84)					−0.004 (−2.17)					0.85
		2.259 (3.11)	0.886 (11.8)	–	–								−3.243 (−3.14)		0.85
	Outlier-adj.	0.105 (1.10)	0.746 (5.32)	–	–				−0.031 (−4.11)						0.57
		1.470 (8.00)	–	–	–					−0.008 (−5.53)					0.52
		0.170 (1.37)	0.581 (3.20)	–	–										0.29
US	Original	0.092 (0.90)	0.729 (5.90)	–	–			−0.046 (−3.85)							0.61
		0.128 (1.14)	0.702 (5.23)	–	–							−0.014 (−2.93)			0.53
		4.645 (2.93)	0.454 (3.08)	–	–								−6.427 (−2.88)		0.53
	Outlier-adj.	0.325 (2.27)	0.420 (2.34)	–	–										0.15
		0.347 (2.57)	0.443 (2.63)	–	–							−0.009 (−2.07)			0.25
		4.393 (3.55)	–	–	–								−5.456 (−3.10)		0.25

Notes: USVIX denotes the US financial uncertainty variable; USVIX(-1) is the one-lagged USVIX variable.; DUSVIX(-1) is the first difference of USVIX variable with one lag; D2USVIX is the second difference of the USVIX variable. USEPU(-1) denotes the US economic policy uncertainty variable, with one lag; D2USEPU is the second difference of the USEPU variable. USDISP denotes the US macroeconomic uncertainty variable; USDISP(-1) is the one-lagged USDISP variable.

Table 3: Regression of country-specific uncertainty variables on GDP growth (2005Q1-2011Q4).

Country	Type	ϕ_0	ϕ_1	ϕ_2	ϕ_3	VIX	VIX(-1)	DVIX(-1)	D2VIX	EPU(-1)	DEPU(-1)	D2EPU	$\overline{R}^2$
Canada	Original	0.161 (1.54)	0.618 (4.98)	–	–			−0.053 (−4.36)					0.61
		0.178 (1.50)	0.647 (4.58)	–	–						−0.010 (−3.13)		0.51
	Outlier-adj.	0.309 (2.46)	0.480 (3.05)	–	–			−0.043 (−3.65)					0.40
		0.321 (2.30)	0.498 (2.79)	–	–						−0.008 (−2.56)		0.27
France	Original	0.124 (1.45)	0.360 (2.29)	0.338 (2.29)	–				−0.033 (−4.35)				0.60
		0.165 (1.58)	0.457 (2.87)	–	–							−0.013 (−2.46)	0.42
	Outlier-adj.	0.486 (6.07)	–	–	–				−0.015 (−2.10)				0.12
		0.491 (6.11)	–	–	–							−0.009 (−2.13)	0.12
Germany	Original	0.283 (1.95)	0.484 (4.19)	–	–			−0.097 (−5.88)					0.67
		0.355 (1.97)	0.411 (2.89)	–	–						−0.036 (−3.96)		0.51
	Outlier-adj.	0.656 (4.23)	0.232 (1.71)	–	–			−0.083 (−5.90)					0.57
		0.860 (5.79)	–	–	–						−0.027 (−3.36)		0.29
Italy	Original	1.326 (4.14)	–	–	–	−0.051 (−4.34)		−0.052 (−3.62)					0.64
		0.071 (0.45)	–	–	–							−0.031 (−3.70)	0.34
	Outlier-adj.	0.141 (1.16)	0.409 (2.08)	–	–								0.12
		0.141 (1.16)	0.409 (2.08)	–	–								0.12
Japan	Original	2.204 (4.00)	–	–	–	−0.079 (−4.11)							0.37
	Outlier-adj.	0.497 (1.93)	–	–									
Netherlands	Original	2.711 (8.20)	–	−0.257 (−2.02)	–	−0.041 (−3.37)	−0.051 (−3.92)						0.72
		0.166 (1.23)	0.572 (4.00)	–	–						−0.019 (−2.90)		0.51
	Outlier-adj.	1.736 (4.80)	–	−0.400 (−1.96)	–		−0.033 (−2.92)						0.25
		1.362 (3.28)	–	–	–					−0.007 (−1.84)			0.09
Spain	Original	0.012 (0.22)	0.870 (12.1)	–	–			−0.024 (−3.88)					0.87
		0.017 (0.25)	0.851 (10.2)	–	–						−0.008 (−2.38)		0.83
	Outlier-adj.	0.111 (1.23)	0.716 (5.20)	–	–			−0.033 (−4.39)					0.60
		0.183 (1.89)	0.650 (4.67)	–	–						−0.013 (−3.84)		0.55

Notes: [a] *The estimation is based on HAC estimator.*

Figure 1: Density for Australia.

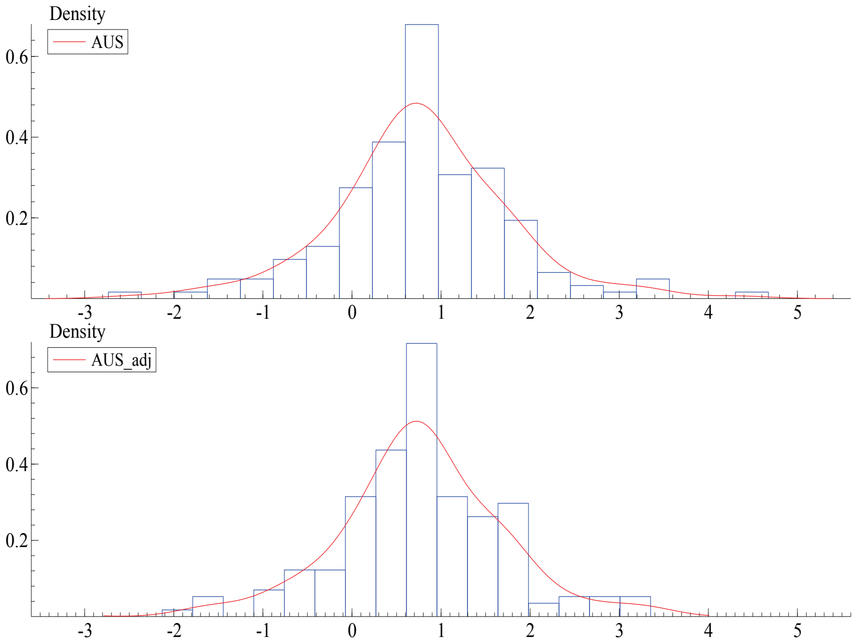


Figure 2: Density for Canada.

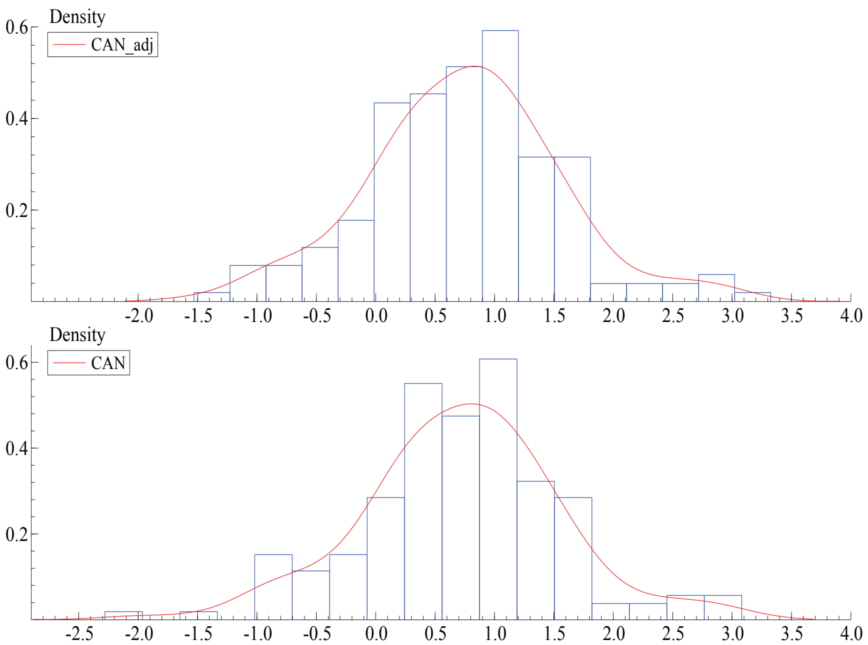


Figure 3: Density for France.

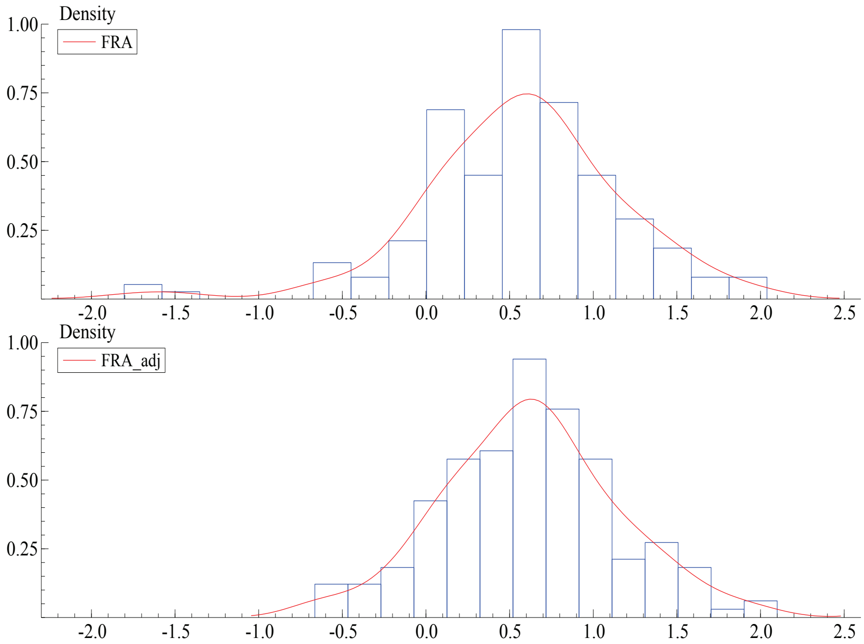


Figure 4: Density for Germany.

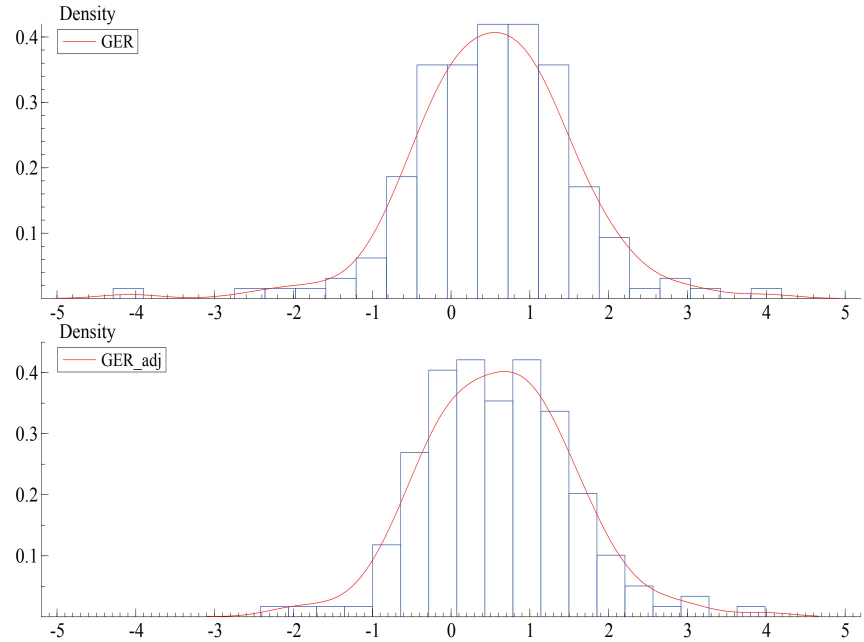


Figure 5: Density for Italia.

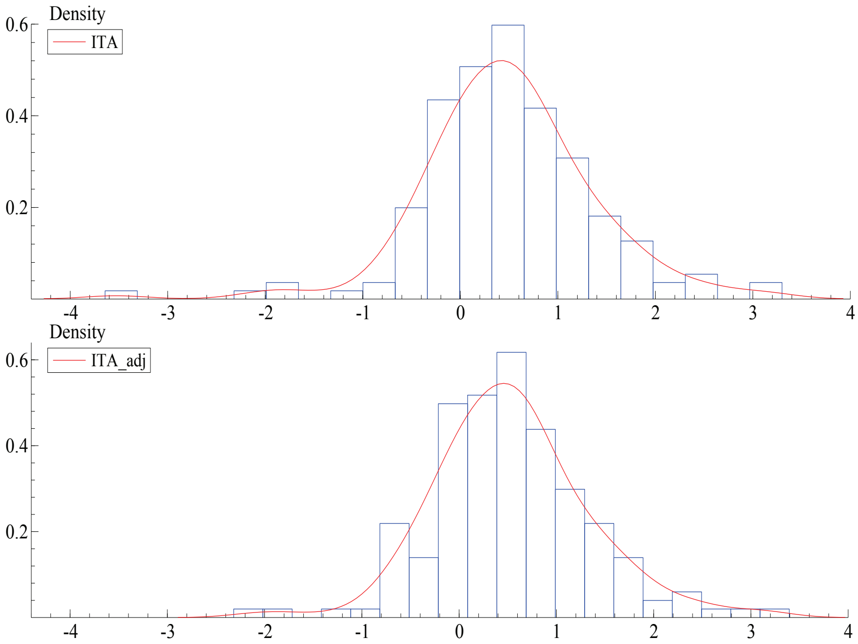


Figure 6: Density for Japan.

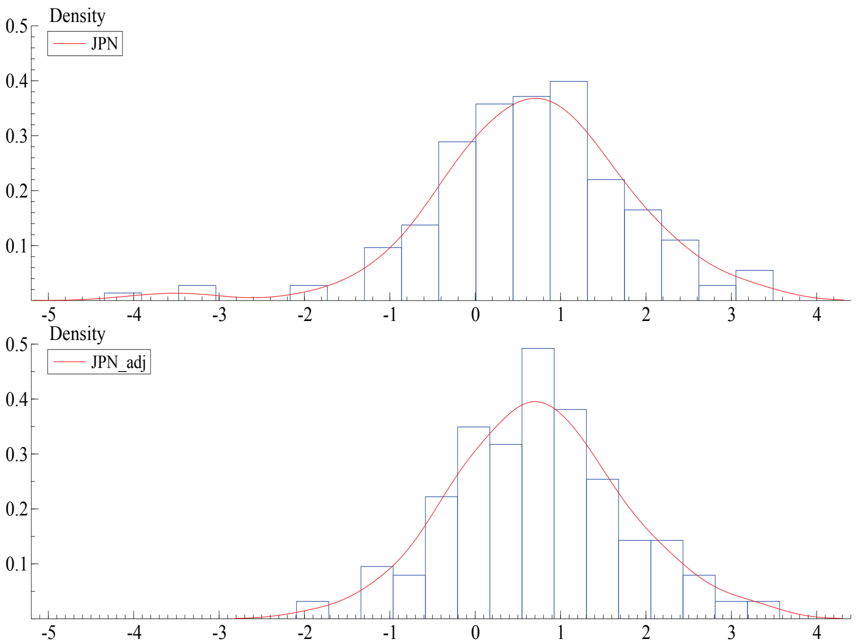


Figure 7: Density for The Netherlands.

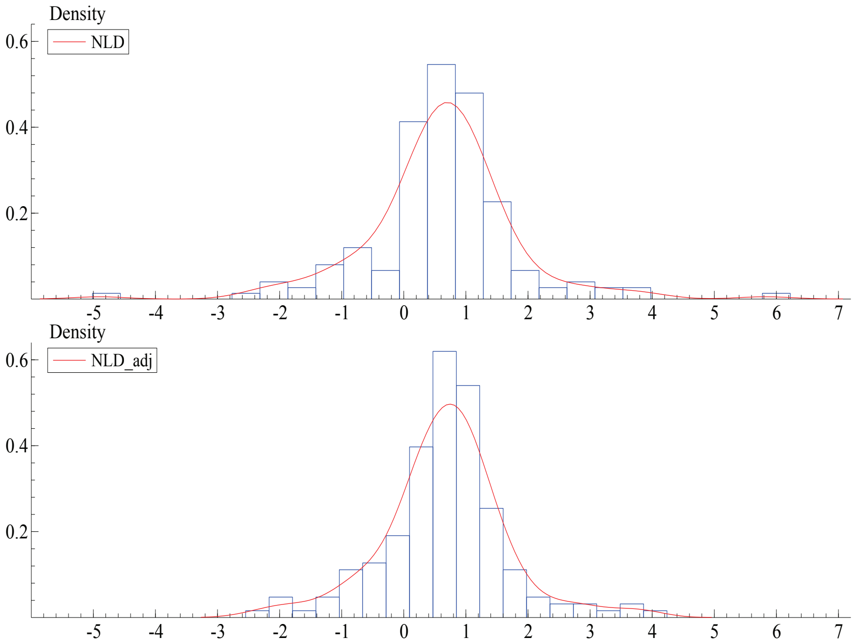


Figure 8: Density for Spain.

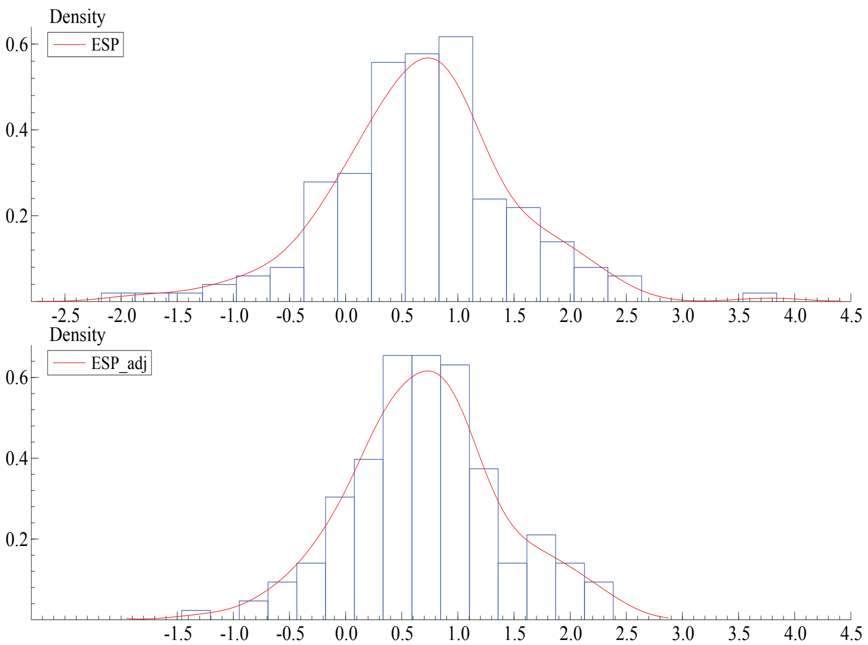


Figure 9: Density for the UK.

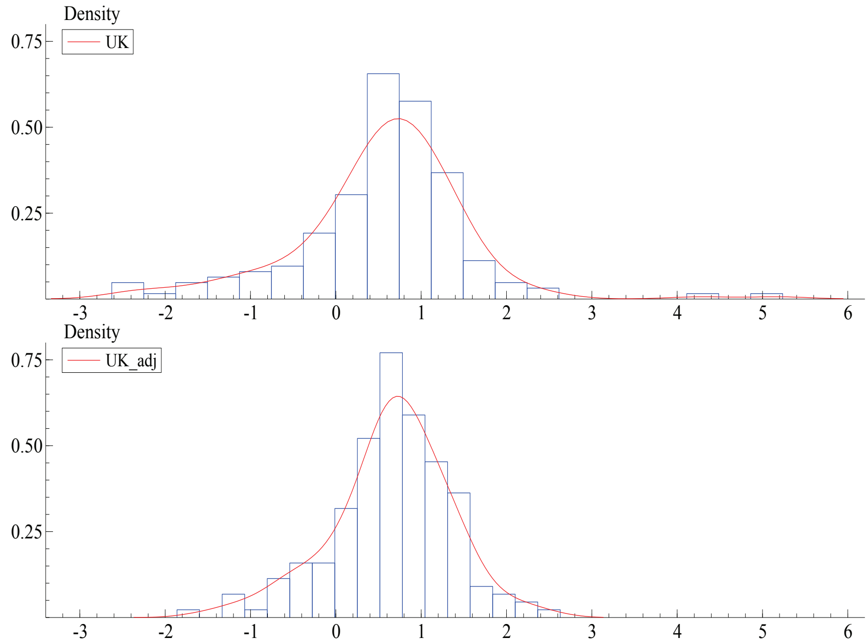


Figure 10: Density for the US.

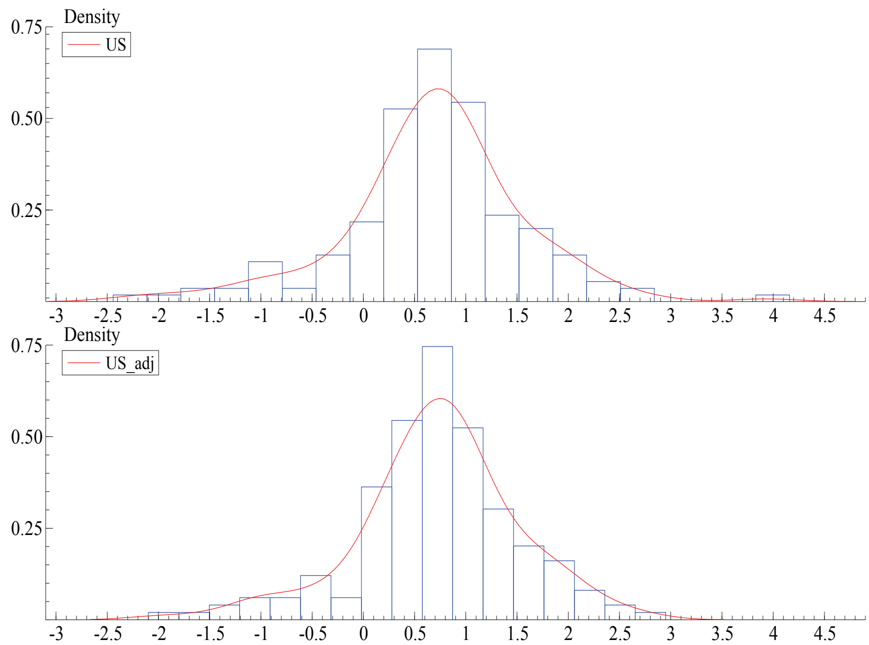
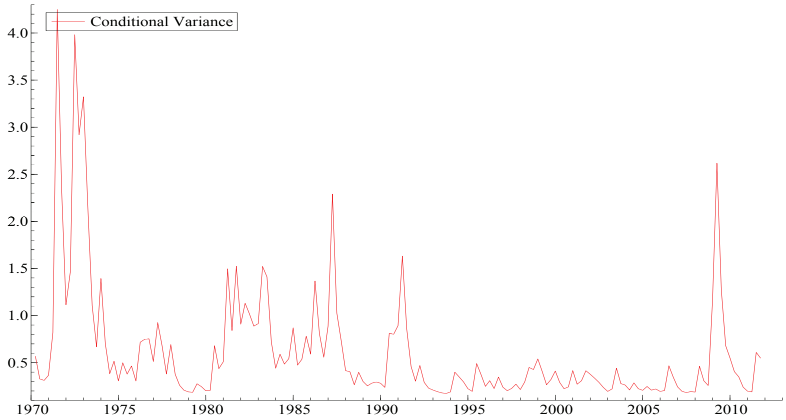
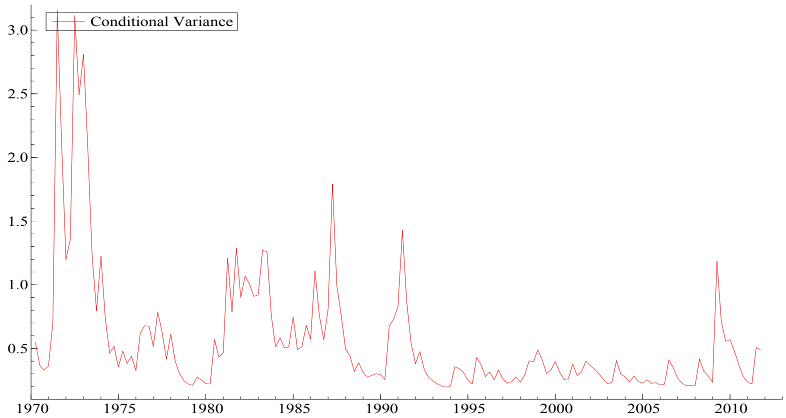


Figure 11: Conditional variance for Canada.





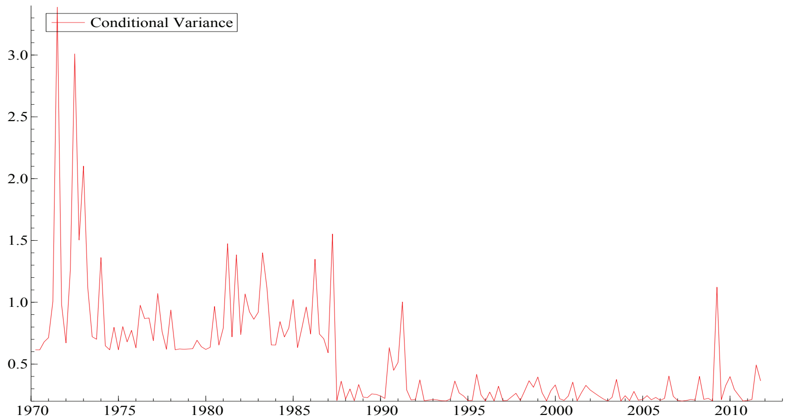
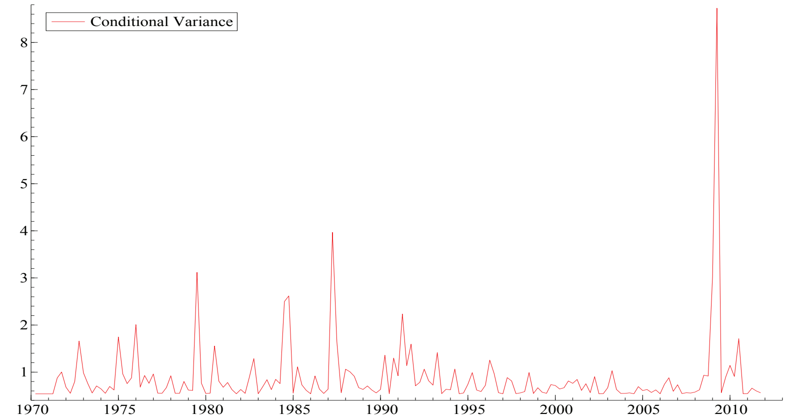


Figure 12: Conditional variance for Germany.



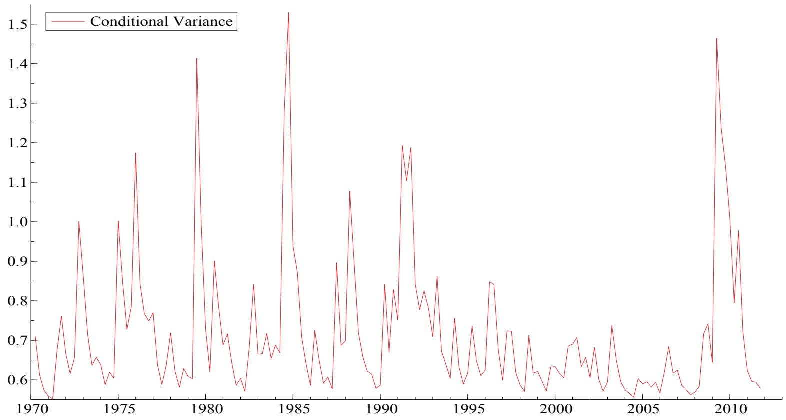


Figure 13: Conditional variance for Italia.

Figure 14: Conditional variance for Spain.