The Great Recession. Worse than ever? *

Maximo Camacho †
University of Murcia

María Dolores Gadea ‡
University of Zaragoza

Gabriel Pérez-Quirós §
Bank of Spain and CEPR

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Abstract

We develop an international comparative assessment of the Great Recession, in terms of the features that characterize the form of the recession phases, namely length, depth and shape. The potential unobserved heterogeneity in the international recession characteristics is modeled by a finite mixture model. Using Bayesian inference via Gibbs sampling, the model classifies the Great Recession suffered by a large number of countries into different clusters, determining its severity in cross section and time series and dimensions. Our results suggest that the business cycle features of the Great Recession are not different from others in an international perspective. By contrast, we show that the only distinctive feature of the Great Recession was its unprecedented degree of synchronicity.

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†Department of Quantitative Analysis, University of Murcia. Campus de Espinardo 30100 Murcia (Spain). Tel: +34 868 887982, fax: +34 868 887905 and e-mail: mcamacho@um.es

‡Department of Applied Economics, University of Zaragoza. Gran Vía, 4, 50005 Zaragoza (Spain). Tel: +34 9767 61842, fax: +34 976 761840 and e-mail: lgadea@unizar.es

§Bank of Spain, Alcalá, 48, 28014 Madrid (Spain). Tel: +34 91 3385333, fax: +34 915310059 and e-mail: gabriel.perez@bde.es

1. Introduction

The Great Recession is a term that refers to the worldwide economic downturn in economic activity during the end of the first decade of the XXI century. The decline was accompanied by a sudden drop in the stock market, a loss in confidence, a (near)bank collapse, an increase in unemployment, and a decline in the housing market.

Perhaps because this recession was the first piece of long-lasting major bad news that has occurred in the social media era, one is tempted to believe that the Great Recession is particular, in the sense that it has been the worst in recent history (Grusky, Western and Wimer, 2011; Katz, 2010; Bagliano and Morana, 2012). Certainly, the Great Recession has been terrible, with consequences on labor markets (Elsby, Hobijn and Sahin, 2010), on international trade (Baldwin, 2010), on income distribution (Jenkins, Brandoline and Micklewright, 2013), and in future growth (Ball, 2014). In addition, the origins of the Great Recession has been the source of a debate. Aiyar (2012) focused on banking propagation, Mian and Sufi (2010) on household leverage, Farmer (2012) on the stock market crash, and Gourinchas and Obsfeld (2011), Mendoza and Terrones (2008) and Claessens et al. (2011) on the role of credit. However, none of these papers measure the relative size of the last recession in cross-section and time-series dimensions.

With the aim of filling this gap in the literature, this paper proposes a comprehensive study that places the Great Recession into a historical and international perspective. From a large set of 42 OECD countries, we start the analysis by collecting their growth rates of GDP, which is considered as a good approximation to their respective aggregate economic activities. Following the lines suggested by Harding and Pagan (2002), we apply the Bry-Boschan quarterly (BBQ) algorithm, Bry and Boschan (1971), to locate their respective turning points, which are used to determine the four items of interest that describe the main business cycle features of an economic downturn: duration, amplitude, cumulation and excess.

The multivariate vectors of characteristics are assumed to arise from a finite mixture of Gaussian distributions, which refer to different subgroups or clusters that are mixed at random in proportion to the relative group sizes. So, the recession features are homogeneous within and heterogeneous across clusters. Following the techniques outlined by Fruhwirth-Schnatter (2006), we use Gibbs sampling to determine the number of clusters, to estimate the parameters that characterize the mean distribution of the clusters, and to perform a data classification, in the sense that each recession is placed in a group, where recessions with similar characteristics are clustered.

In the cross-section analysis, our results suggest that there are two groups of countries, attending to their recession characteristics. In the first group of developed countries, recessions are smooth and mild. In the second group of countries, recessions are more long-lasting and severe. However, in both groups, the excess is positive, which means that recessions are concave.

In the time-series analysis, we find that the Great Recession occurred in 37 of the 42 countries analyzed. However, in about 40% of these the Great Recession appears in a group "normal recessions" instead of in the group of "big recessions". The unique distinctive characteristic of the Great Recession is its unprecedented degree of synchronization.

The paper is structured as follows, Section 2 proposes the methodology, define the characteristics and describes the clustering methods. Section 3 presents the empirical results and, finally, Section 4 concludes.

2. METHODOLOGY

2.1. Business cycle characteristics

We refer to business cycles as the short-term periodic but irregular up-and-down movements in GDP, which is viewed as the most comprehensive measure of the overall economic activity. A typical business cycle has two phases, the expansion phase or upswing and the contraction phase or downswing. At some date, called a peak, GDP reaches its upper turning point and a contraction phase begins as GDP starts to decline. After some (typically short) time of contraction, GDP reaches its lower turning point, known as a trough, and an expansion begins as GDP growth rates become positive values. Obviously, these ups and dows are full of local minima and maxima due that GDP is a noisy signal of the underlying cycle that we try to measure.

In order to clean up the noise, in our empirical implementation, we compute the specific business cycle turning points chronologies by applying the Harding and Pagan (2002) non-parametric dating procedure, which extends the seminal Bry and Boschan (1971) monthly dating to a quarterly frequency. This algorithm consists of a set of filters and rules that isolates the local minima and maxima in the log levels of the national series of seasonally-adjusted GDP, subject to constraints on both the length and amplitude of expansions and contractions.[1]

In short, the Harding-Pagan dating algorithm requires three simple decision rules. First, the procedure determines a potential set of local minima and maxima. Second, peaks and troughs must alternate leading to expansions (periods from troughs to peaks) and recessions (period from peaks to troughs). Finally, a set of censoring rules ensures that some predetermined criteria concerning the duration and amplitudes of phases and complete cycles are satisfied. For example, a complete cycle, from peak to peak or from trough to trough, must have a duration of at least four quarters. Finally, the algorithm does not consider turning points within six months of the beginning or end of the GDP series.

Once the turning points have been established, we focus on the analysis of features that characterize the recession phases of country c ($c = 1, ..., \widetilde{C}$), related with length, depth and shape and define the duration (D), amplitude (A), cumulation (C) and excess (E). The first feature that characterizes a j-th recession from the set of the J recessions of that country is duration, which refers to the time spent between the j-th peak (P_{cj}) and the following trough (T_{cj}). Then, the duration is computed as $D_{cj} = T_{cj} - P_{cj}$ and the averaged duration as $D_c = \frac{1}{J}\sum_{j=1}^{J} D_{cj}$ where j refers to the j-th recession and c refers to country "c".

The second feature is the amplitude of the recession. If $y_{P_{cj}}$ and $y_{T_{cj}}$ are the log level of GDP

[1]Therefore, business cycle recessions refer to declines in GDP, and not to periods of slow growth relative to a trend or growth-cycle recessions.

at the j-th peak and the j-th trough, respectively, the amplitude is defined as $A_{cj} = y_{T_{cj}} - y_{P_{cj}}$. Multiplied by 100, the amplitude represents the percentage of total loss of the downturn in terms of GDP. The averaged amplitude is computed as $A_c = \frac{1}{J}\sum_{j=1}^{J} A_{cj}$.

The third key dimension of a recession, cumulation, measures its severity through the cumulative falls in economic activity within the downturn. Harding and Pagan (2002) propose computing cumulation as $C_{cj} = -\left(\sum_{h=1}^{D_{cj}} \left|y_{P_{cj}+h} - y_{P_{cj}}\right| - 0.5A_{cj}\right)$, where the term $0.5A_{cj}$ removes the bias due to the approximation of a triangle by a sum of rectangles. In this work, it is calculated by approaching, by numerical methods, the integral of the area described by the evolution of log level of GDP between $y_{P_{cj}}$ and $y_{T_{cj}}$, $C_{cj} = \int_{P_{cj}}^{T_{cj}} y dy$. In the same fashion, the averaged cumulation can be obtained as $C_c = \frac{1}{J}\sum_{j=1}^{J} C_{cj}$.

The last feature of a recession is the excess and measures its shape. This feature can be viewed as measuring the departures of the actual GDP path from the hypothetical path if the transition between the peak and the trough was linear, i.e., $E_{cj} = C_{cj} - 0.5D_{cj}A_{cj}$. Positive excess indicates that actual paths exhibit gradual changes in the slope at the beginning of the recession, but they become abrupt as the end of the phase comes. Negative excess refers to recessions with abrupt losses at the beginning and smooth falls at the end. Finally, the averaged excess in country c is $E_c = \frac{1}{J}\sum_{j=1}^{J} E_{cj}$.

2.2. Clustering by recession characteristics

The potential unobserved heterogeneity in recession characteristics for a set of $\widetilde{C}$ countries is modeled by using a finite mixture model. We denote $x_c = (D_c, A_c, C_c, E_c)$ as the vector of averaged characteristics for country c and $x_{cj} = (D_{cj}, A_{cj}, C_{cj}, E_{cj})$ as the vector of characteristics of the j-th recession of country c, where $j = 1, \ldots, J_c$ and $c = 1, \ldots, \widetilde{C}$. Now, let y_i be the matrix of characteristics that refers to x_c in the case of the averaged characteristics and to x_{cj} in the case of the j-th specific characteristics analysis, where $i = 1, \ldots, N$ ($i = 1, ..., \widetilde{C}$ in the case of averaged characteristics and $i = 1, ..., J_{\widetilde{C}}$ in the case of specific characteristics).

The multivariate vectors of characteristics y_i are assumed to arise from a mixture of K distinct distributions. Therefore, each component probability distribution corresponds to a separate cluster and the business cycle characteristics are heterogeneous across clusters and homogeneous within them. We assume that each cluster is characterized by a multivariate Gaussian density, parameterized by its mean μ_k and its covariance matrix Σ_k, which are collected in the vector θ_k.

The probability density function of the mixture model is

$$f\left(y_i|\theta_k\right) = \sum_{k=1}^{K} \tau_k N\left(\mu_k, \Sigma_k\right), \tag{1}$$

where $i = 1, \ldots, N$, and τ_k are the mixing proportions or weights and represent the proportion of observations from each cluster, with $\tau_k \geq 0$, and $\tau_1 + \ldots + \tau_K = 1$.

To view the mixture model as a hierarchical latent variable model, the observations are labeled through an unobservable latent variable s taking values in the discrete space $\{1, 2, \ldots, K\}$ in the whole sequence of realizations, which are collected in $S = (s_1, \ldots, s_N)$. The latent variable allows us to identify the mixture component each observation has been generated from: if $s_i = k$, then the observation i of multivariate characteristics belongs to cluster k.

The estimation of the parameters in vector $\theta = (\theta_1, \ldots, \theta_K)$, the mixing proportions $\tau = (\tau_1, \ldots, \tau_K)$, and the inference on s, is performed through a Markov Chain Monte Carlo (MCMC) method. The Gibbs sampler used to implement the MCMC starts with a preliminary classification $S^0 = \left(s_1^0, \ldots, s_N^0\right)$ obtained by applying the $k-$means clustering algorithm with K clusters. The algorithm also gives the number of observations assigned to each $k-$th cluster, $N_k\left(S^0\right)$, and its within-group mean μ_k.

Then, the distribution of the parameters can be approximated by the empirical distributions of simulated values, by iterating the following two steps for $m = 1, \ldots, M_0, M_0 + 1, \ldots, M_0 + M$. Formally, the next three steps need to be followed:

STEP 1. Sample the model parameters $\theta^{(m)}$ and $\tau^{(m)}$ conditional on the classification $S^{(m-1)}$. Assuming independence, when sampling the transition probabilities, the Dirichlet distribution is the standard choice in the context of modeling discrete weight distributions. Based on assuming a Dirichlet prior $\tau \sim D\left(e_1, \ldots, e_K\right)$, the posterior distribution of the weight distributions conditional on the classification is also a Dirichlet $\tau|S \sim \left(e_1\left(S\right), \ldots, e_K\left(S\right)\right)$, where

$$e_k\left(S\right) = e_k + N_k\left(S\right). \tag{2}$$

and $N_k\left(S\right)$ is the number of observations and the mean in group k.

In sampling *theta*, we work with the assumption that means and covariance matrices are independent of one another. Under the standard Normal-Wishart prior for each (inverse) covariance matrix, $\Sigma_k^{-1} \sim W\left(c_0, C_0\right)$, the posterior distribution is $\Sigma_k^{-1}|S, \mu_k \sim W\left(c_k\left(S\right), C_k\left(S\right)\right)$, where

$$c_k\left(S\right) = c_0 + N_k\left(S\right), \tag{3}$$

$$C_k\left(S\right) = C_0 + \sum_{i:s_i=k}\left(\mu_i - y_i\right)\left(\mu_i - y_i\right)'. \tag{4}$$

Under the Normal prior for the means $\mu_k \sim N\left(b_0, B_0\right)$, when holding the covariances fixed, the posterior density for the mean is again a density from the normal distribution $\mu_k|S, \Sigma_k \sim N\left(b_k\left(S\right), B_k\left(S\right)\right)$, where

$$B_k\left(S\right) = \left(B_0\left(S\right)^{-1} + N_k\left(S\right)\Sigma_k^{-1}\left(S\right)\right)^{-1}, \tag{5}$$

$$b_k = B_k\left(S\right)\left(B_0^{-1}b_0 + \Sigma_k^{-1}\sum_{i:s_i=k} y_i\right). \tag{6}$$

STEP 2. Sample the path of allocations $S^{(m)}$ conditional on observations and model parameters by running the multi-move Gibbs sampler. From STEP 1, determine the state probability distribution for each observation

$$p\left(S_i = k|y_i, \theta\right) = \frac{\tau_k N\left(\mu_k, \Sigma_k\right)}{\sum_{k=1}^{K} \tau_k N\left(\mu_k, \Sigma_k\right)}. \tag{7}$$

Then, for each observation, generate a random number, u_i, from a uniform distribution between 0 and 1, and compute w_i as the number of times that $\sum_{k=1}^{k^*} p\left(S_i = k|y_i, \theta\right) < u$, with $k^* = 1, 2, \ldots, K$. Finally, sample s_i^m as $1 + w_i$.

STEP 3. Apply a random permutation of the current labeling of the clusters of the latent process. As documented by, among others, Fruhwirth-Schnatter (2001), the unconstrained posterior of the general switching and mixture model could have $K!$ different modes. Accordingly, the unconstrained MCMC sampler could have unidentifiability problems. Following this author, we propose a random permutation sampler in which the unrestricted MCMC sampler is concluded by a permutation of the indices of the clusters.

For this purpose, select a random permutation $\rho_m = \{\rho_m(1), \ldots, \rho_m(K)\}$ of the labeling of the clusters $\{1 \ldots, K\}$ and reorder the labeling of the cluster-specific parameters, the weights, and the latent process through this permutation. The relabeling leads to $\{\theta_{\rho_m(1)}, \ldots, \theta_{\rho_m(K)}\}$, $\{\tau_{\rho_m(1)}, \ldots, \tau_{\rho_m(K)}\}$, and $\{s_1^m(\rho_m), \ldots, s_N^m(\rho_m)\}$. Now, the actual values of all allocations are stored according to $S^{(m)}$, and the iterations return to STEP 1 $M_0 + M$ times, although the first M_0 draws are discarded.

Parameters estimation is achieved by applying a standard $k-$means clustering algorithm with K clusters to the sample of size MK formed from the MCMC draws. In addition, the clustering algorithm delivers a classification sequence that determines to which cluster each observation belongs.

2.3. Identifying the number of components

Finally, we have to decide on the selection of the number of components of the mixture model, K, from the data. Despite the amount of work developed in this area, choosing the number of clusters is still unsolved. With the aim of robustness, we follow three different approaches in practice. Let M_K be a mixture model of k components and $\widehat{\theta}_K$ the $d-$dimensional vector of its maximum likelihood estimated parameters. Let $\log f\left(y|\widehat{\theta}_K, M_K\right)$ be the marginal log likelihood function.

Among the likelihood-based methods, the simplest case is choosing the model with the number of components K that reaches the highest marginal likelihood over a set of potential values of $\{1, \ldots, K^*\}$, where the upper bound K^* is specified by the user. Since this method tends to choose models with a large number of components, we also consider selecting criteria that introduce an explicit penalty term for model complexity. For reasons of parsimony, we use the Akaike model choice procedure, which is commonly implemented by choosing the value of K for which $AIC_K = -2lf\left(y|\widehat{\theta_K}, M_K\right) + 2d_K$ reaches a minimum. In addition, we consider the Schwartz's criterion of selecting the number of components that minimizes $BIC_K = -2\log f\left(y|\widehat{\theta}_K, M_K\right) + d_K \log(N)$.

We also base the selection of the number of components by choosing the model with the number of components that maximizes the quality of the classification. For this purpose, we define the entropy as

$$EN_k = -\sum_{i=1}^{N}\sum_{k=1}^{K} p\left(S_i = k|y_i, \theta\right) \log p\left(S_i = k|y_i, \theta\right), \tag{8}$$

which measures how well the data are classified given a mixture distribution. The entropy takes the value of 0 for a perfect partition of the data and a positive number that increases as the quality of the classification deteriorates.

One interesting option is to combine the aim of selecting a model with an optimal number of components as likelihood-based methods propose with the aim of obtaining a model with a good partition of the data as proposed by model selection criteria based on entropy measures. For this purpose, we also consider $BIC_K - EN_k$ as a metric that penalizes not only model complexity but also misclassification.

Finally, we consider the Bayes factor to compare two models M_1 and M_2 with different number of components K_1 and K_2. Among others, Kass and Raftery (1995) define

$$B_{12} = \frac{f\left(y|\widehat{\theta}_1, M_1\right)}{f\left(y|\widehat{\theta}_2, M_2\right)}, \tag{9}$$

as a measure of the extent to which the data increase the odds on M_1 relative to M_2. These authors suggest interpreting B_{12} in units on the $-2\log B_{12}$ scale and state that values of this metric above ten indicate very strong evidence in favor of model M_2.

3. Empirical Results

3.1. *Dating the cycles*

We use a wide sample of 42 OECD countries from 1947 to 2017 for the quarterly GDP growth.[2] We focus on these countries because their respective sample size is large enough to guarantee a sufficient number of turning points for dating the business cycle. Figure 1 displays the evolution of GDP growth of the selected set of countries.

In a first step, we obtain the business cycle chronology using the BBQ algorithm described in

[2]The sources are OECD, Datastream and National Statistics Institutions. The series employed is the Gross Domestic Product, expenditure approach, volume estimates in millions of national currency, quarterly and seasonally adjusted. The countries and their codes according with ISO 3166-1 code alpha 3 are 'Argentina' (ARG), 'Australia' (AUS), 'Austria' (AUT), 'Belgium' (BEL), 'Brazil' (BRA), 'Canada' (CAN), 'Chile' (CHL), 'Costa Rica' (CRI), 'Cyprus' (CYP), 'Czech Republic' (CZE), 'Denmark' (DNK), 'Estonia' (EST), 'Finland' (FIN), 'France' (FRA), 'Germany' (DEU), 'Greece' (GRC), 'Hungary' (HUN), 'Iceland' (ISL), 'Indonesia' (IDN), 'Ireland' (IRL), 'Israel' (ISR), 'Italy' (ITA), 'Japan' (JPN), 'Korea' (KOR), 'Latvia' (LVA), 'Lithuania' (LTU), 'Luxembourg' (LUX), 'Malta' (MLT), 'Mexico' (MEX), 'Netherlands' (NLD), 'New Zealand' (NZL), 'Norway' (NOR), 'Portugal' (PRT), 'Slovak Republic' (SVK), 'Slovenia' (SVN), 'South Africa' (SAF), 'Spain' (ESP), 'Sweden' (SWE), 'Switzerland' (CHE), 'Turkey' (TUR), 'United Kingdom' (GBR), 'United States' (USA).

Section 2 for each individual country. Figure 2 displays the evolution of the GDP and highlights the periods of recession with shaded bars. Using these turning points, Figure 3 shows the percentage of periods that each country is in recession. Some countries stand out for remaining in recession considerably longer than the average, which is 13.19%, ARG, BRA and GRG. Another group of countries presents of higher-than-average duration of recessions is BYP, FIN, HUN, ISL, ITA, LVA and NZL. In addition, NLD, PRT and SAF remain in recession just slightly above the average. In contrast, among those countries with shortest recessions we find CAN, CHL, CRI, FRA, IDN, KOR and SVK.

In a second step, we follow the lines suggested by Harding and Pagan (2002) and disentangle and characterize cyclical phases, singling out recessions.[3] In particular, we focus on duration, amplitude, cumulation and excess, which are displayed for each country in Figure 4. The mean duration of the recessions is 4.45 quarters.[4] However, we find some heterogeneity in the duration of recessions across countries. CYP, GRC and IRL present long-lasting recessions (more than 7 quarters) while CRI MLT, KOR, AUT, DEU and USA spend on average less than 3 quarters in each recession. Clear cross-country asymmetries in the amplitude of the phases of the cycle are also observed. Expressed in percentages, this measure, which shows the loss in GDP as a result of recessions, has a averaged value of 4.79%. IDN, EST, LTU, LVA and TUR stand out for having values well above the average, especially IDN with more than 20%. On the contrary, BEL, AUT, AUS and COL undergo from shallow recessions.

Cumulation is a measure used to identify the accumulated loss, calculated as the sum of the amplitudes for each period of the phase. It is very useful as it can be interpreted as the loss of wealth in the economy in percentage of GDP, and synthesizes the previous measures by combining the duration, amplitude and shape of the business cycle. According to this measure, GRC, IDN, EST, LVA, ARG and CYP can be highlighted for the severity of their recessions while AUT, BEL, MLT, CRI for their smoothness.

The difference between the actual shape of the recession and its triangle approximation is measured as excess. Positive excess dominates during most recessions, so the shape of the wealth loss is mainly concave. Consequently, the paths of the aggregate activity exhibit gradual changes at the beginning of the phase that become sharp at the end. On the other hand, countries with convex recessions as CYP, LVA, SVK, and LTU, exhibit large declines in economic activity at the beginning of the recessions, that become smoother as the recessions end.

To examine the international disparities in the distribution of the recession characteristics, Figure 5 displays the box-plot representation of them. For each characteristic, the bottom and top of the box are the first and third quartiles, the band inside the box refers to the median and the bottom and top horizontal lines refer to the minimum and maximum values, excluding outliers,

[3]The detailed tables of expansion and recession characteristics for each country are available upon request.

[4]Just to put these figures in context, they closely agree with the estimated duration of business cycle phases proposed by the NBER for the 33 cycles in the recent history of the US (1854-2009), which is 17.5 months -11.1 months if we only include the 11 cycles after the WWII- (see http://www.nber.org/cycles/cyclesmain.html). According to Camacho *et al.* (2006), European recessions last about 15 months.

which are plotted individually using the '+' symbol. The box-plots show that the highest disparities in the distribution of characteristics appear in cumulation and amplitude while the distribution of excess and duration are more homogeneous. However, these figures also show significant outliers in the distribution of cumulation, and excess, and, in a lesser extent, in the distribution of amplitude. Finally, the box-plots show that the distribution of duration is negative skewed while the distribution of amplitude and cumulation are positively skewed.

3.2. Clustering countries by recession characteristics

In this section we apply the mixture model approach to group the countries by their averaged recession characteristics: duration, amplitude, cumulation and excess. The first stage in this modeling approach is determining the number of groups of countries that are cohesive in terms of their recession characteristics. For this purpose, we estimate a set of models M_k for $K = 1....Kmax$, with $Kmax = 4$, and compute the measures described in Section 2.3 for each k.[5] For each k, Table 1 reports the estimated marginal likelihoods, the likelihood-based methods, the entropy, the misclassifcation-corrected BIC and the Bayes factors. Although the likelihoods increase and AIC decreases with the number of clusters, the great jumps occurs when the number of clusters is $k = 2$. In addition, BIC, EN and BIC-EN select $k = 2$. Finally, although the sequence of Bayes factors also point to $k = 4$ because the value of BF is above ten when we consider $k = 2$ versus $k = 3$ and $k = 3$ versus $k = 4$, the great gain in BF appears when the model with $k = 1$ is compared with the model $k = 2$.[6] According to these results, we choose $k = 2$.

The results of the estimated mixture model for $k = 2$, with the help of the random permutation Gibbs sampler, are displayed in Table 2. In short, the first group is characterized by countries having smooth recessions, which are short lived, and shows relatively low losses in output. The second group of countries exhibits more severe recessions, with higher values of duration, amplitude and cumulation. In both cases, the excess is positive, which means that recessions are concave, starting with a gradual decrease in GDP growth and ending more abruptly, although this behavior is more intense in the second group. About 57% of countries belong to the first group and 43% of the countries belong to the second group. Using the outputs of the MCMC algorithm, this table also shows confidence intervals for the different figures. As we expected, the uncertainty is higher in the second group, which shows wider confidence intervals.

Figure 6 displays two-dimensional scatter plots of the MCMC draws $\left(\mu_i^{(m)}, \mu_{i'}^{(m)}\right)$ for each of the $i = 1, \ldots, 4$ characteristics. The figure shows that duration presents the highest ability to divide the draws into two separate groups, followed by cumulation and amplitude. However, excess is nearly identical for the two groups, being the less useful characteristic for group identification.

The ability of the variances to separate the two groups is examined in Figure 7, which displays the scatter-plot of the MCMC draws $\left(\mu_i^{(m)}, \Sigma_{ii}^{(m)}\right)$. Clearly, the mean exhibits better classification

[5] We set the maximum number of clusters to 4 because our sample contains only 42 vectors of characteristics.

[6] Basically, the MCMC with $k = 4$ splits the two groups obtained with $k = 2$ into two sub-groups, with little differences between them and with a less clear partition.

power than the variance, with the exception of excess, for which the variance separates the groups better than the mean.

Finally, Figure 8 sketches the geographical distribution of the two clusters. An eye-ball examination of the map allows us to identify group 1 (normal recessions) with more developed countries and group 2 (big recessions) with less developed countries. Nevertheless, there are some noticeable exceptions, as the cases of FIN and SWE. In these two countries, the recession characteristics increase dramatically due to the severe recessions at the beginning of the 1990s and which, consequently, place them in group 2.[7] The case of AUS also deserves a separate mention, since this country did not register the impact of the Great Recession but suffered from a serious crisis in the mid-70s, which increases its average. Regarding the distribution of the Great Recession, it occurs in 38 of the 42 countries analyzed, 13 in group 1 and the remaining 25 in group 2.

3.3. Clustering recessions

In this section, we examine all the recessions individually, by looking for clusters in the time dimension, which allows us to place the Great Recession in the recent international history. In particular, we collect the characteristics of a total of 224 recessions in the 42 countries analyzed, and the distribution is examined in the box-plot Figure 9. The figure shows a higher heterogeneity than in the case of the country averages.

Table 3 helps us to determine the number of clusters. Using a a $Kmax$=8, AIC, BIC and EN would select K=8, K=5, and K=3, respectively. The sequence of Bayes factors registers its greatest increase for K=3 although it increases for K=6. Therefore, the decision is between K=3 or higher number of clusters like 5, 6 or 7.

We proceed, first, with K= 3 whose estimates appear in Table 4. We identify a first group of "outliers" that includes 2.54% of the recessions; a second group of "big recessions" that comprises the 29.69% of recessions, and a third group of "normal" recessions that collects the rest, 67.77% of recessions. In the first group, we find the most long-lived, deep and severe international recessions of our OECD sample, which correspond to ARG and GRC. The second group includes recessions that last one third of the duration in the first group, are one fourth as deep as those of the first group and implies one tenth of the their losses. The shortest and mildest recessions appear in the third group.[8] To facilitate international comparisons, Figure 10 displays the classification of the three different groups of recessions by countries.

Figure 11 displays the scatter-plot of the MCMC draws of pairs of means of characteristics. The distribution of draws show three separated groups, with enormous differences in the dispersion of the draws around the group cores. As in the case of average characteristics per country, duration is

[7] These recessions, much more intensive than the Great Recession in these countries, are related with crises and reforms of the Welfare State. Norway's natural petroleum resources prevented a similar crisis in another of the Nordic countries.

[8] If we selected K=6, we would obtain similar big groups of "normal" and "big" recessions and four groups for outliers that would correspond to the specific recessions of ARG, AUS-BRA, GRC and LVA. If we selected K=7, the group of AUS-BRA would be split into in two groups of only one recession. Then, we decide to carry out the rest of the analysis with K=3.

the characteristic that has the greatest capacity to separate the three groups, followed by amplitude and cumulation, while excess is the least useful to form clusters. Figure 12 reports the draws of pairs of means and variances for each characteristic, emphasizing the superior ability of the mean to classify the clusters.

The Great Recession occurs in 37 of the 42 countries analyzed. To place this recession in an historical dimension around the world, Figure 14 plot the classification of the Great Recession for each country across the three groups identified in the mixture model. In about 60% of the countries, the Great Recession is classified in Group 2 of "big recessions". This implies that for about 40% of countries in the sample, the Great Recession appears in Group 3 of "normal recessions". Therefore, the Great Recession is not an exceptionally bad downturn event when it is compared with other recessions that have occurred in developed countries.

Then, why does the Great Recession has been considered by academic, politicians, and the press as "the worst" in recent history? According to our results, the answer is not in its characteristics. We show that the feature that convert the Great Recession in a rare event is its synchronicity. To address the degree of synchronization of the Great Recession, we compute a recession indicator for each country, $I_{i,t}$, that takes the value of one if country i is in recession at time t, according to the Bry-Boschan algorithm. Then we compute an index of recession synchronization as the cross-country average of recession indicator for each country, $SI_t = \frac{1}{N}\sum_{i=1}^{N} I_{i,t}$. Figure 13 displays the index of recession synchronization in OECD countries (grey points) and its 95% confidence intervals (black bars with whiskers). According to this figure, the Great Recession is the recession that produces the greatest synchronization in the OECD countries, well above other major crises in the post-WWII period like those of the seventies. Specifically, the synchronization reached the value of 0.9 in 2008 with a confidence interval of (0.82, 0.99). Then, the only distinctive characteristic of the Great Recession is its unprecedented degree of synchronization.

4. CONCLUSIONS

How bad was the Great Recession compared to past recessions in an historical international perspective? We develop a comprehensive review of the economic recessions suffered by a large set of countries to show that the Great Recession is not different from others in an international perspective in terms of its length, depth and shape. By contrast, we show that the distinctive feature of the Great Recession was its unprecedented degree of synchronicity since it affected almost all the countries of our sample at about the same time.

References

[1] Aiyar,S. (2012): "From Financial Crisis to Great Recession: The Role of Globalized Banks". *American Economic Review*, vol. 102(3), pp. 225-230.

[2] Bagliano, F. and Morana, C. (2012): "The Great Recession: US Dynamics and Spillovers to the World Economy". *Journal of Banking and Finance*, vol. 36(1), 1-13.

[3] Baldwing, R. (2010): "The Great Trade Collapse: What Caused it and What Does it Mean?". In The Great Trade Collapese: Causes, Consequences and Prospects. CEPR. VoxEU.org Publication.

[4] Ball, L (2014): "Long-term damage from the Great Recession in OECD countries". *European Journal of Economics and Economic Policies: Intervention*, Edward Elgar, vol. 11(2), pp. 149-160.

[5] Bry, G. and Boschan, Ch. (1971): *Cyclical Analysis of Time Series: Selected Procedures and Computer Programs*. New York, NBER.

[6] Camacho, M., Pérez-Quirós, G. and Saiz, L. (2006): "Are European business cycles close enough to be just one?", *Journal of Economic Dynamics and Control*, vol.30, 1687-1706.

[7] Claessens, S., Kose, A. and Terrones, M.E. (2011): "How do business and financial cycles interact?". CEPR DP8396.

[8] Elsby, M., Hobijn, B. and Sahin, A. (2010): "The Labor Market in the Great Recession" NBER Working Paper. No 15979.

[9] Farmer, R. (2012): "The stock market crash of 2008 caused the Great Recession: Theory and evidence". *Journal of Economic Dynamics and Control*, vol. 36(5), pp. 693-707.

[10] Frühwirth-Schnatter, S. 2001. Markov Chain Monte Carlo estimation of classical and dynamic switching and mixture models. *Journal of the Americal Statistical Association*, vol. 96(453), pp. 194-209.

[11] Frühwirth-Schnatter, S. 2006. *Finite Mixture and Markov Switching models*. Springer Series in Statistics. New York, NY: Springer.

[12] Gourinchas, P.O. and Obstfeld, M. (2011): "Stories of the Twentieth Century for the Twenty-First". American Economic Journal: Macroeconomics vol. 4(1), pp. 226-265.

[13] Grusky, D. B., Western, B. and Wimer, C. (2011): "The Consequences of the Great Recession". In *The Great Recession*. Russell Sage Foundation. New York

[14] Harding, D. and Pagan, A. (2002): "Dissecting the cycle: A methodological investigation". *Journal of Monetary Economics* vol. 49(2), pp. 365-381.

[15] Jenkins, S., Brandolini, A and Micklewright J. (2013): "The Great Recession and its consequences for household incomes in 21 countries". In *The Great Recession and the Distribution of Household Income*. Oxford University Press.

[16] Katz. L. (2010): "Long-Term Unemployment in the Great Recession". Testimony for the Joint Economic Committee U.S. Congress.

[17] Kass, R., and Raftery, A. 1995. Bayes factors. *Journal of the American Statistical Association* vol. 90(430), pp. 773-795.

[18] Mian, A. and Sufi, A. (2010): "The Great Recession: Lessons from Microeconomic Data". *American Economic Review: Papers & Proceedings*, vol. 100(2), pp. 1-10.

[19] Mendoza, E.G. and Terrones, M.E. (2008): "An anatomy of credit booms: evidence from macro aggregates and micro data". NBER working paper 14049.

Tables

Table: 1: Number of components (averaged characteristics)

K	LogLik	AIC	BIC	EN	BIC-EN	Bayes factor (k=i/k=i+1)
1	-426.00	880.00	904.33	0	904.33	160.18
2	-345.91	751.82	803.95	1.47	806.90	48.26
3	-321.78	733.56	811.76	3.48	818.73	39.22
4	-302.17	724.35	828.61	1.65	831.90	-

Notes. The first column refers to the marginal log likelihoods, the second and third columns refer to the Bayesian AIC and BIC selection criteria, the third column shows the entropy, the fourth column shows the BIC corrected by misclassification, the last column shows the Bayes factor.

Table: 2: Estimated parameters (averaged characteristics)

Parameter	Estimates	
	Group 1 (normal recessions)	Group 2 (big recessions)
	Duration	
$\widehat{\mu}$	3.68 (3.29,4.09)	5.47 (4.77,6.17)
	Amplitude	
$\widehat{\mu}$	-3.07 (-3.57,-2.65)	-7.08 (-9.18,-4.94)
	Cumulation	
$\widehat{\mu}$	-6.90 (-8.40,-5.50)	-26.96 (-34.40,-19.00)
	Excess	
$\widehat{\mu}$	0.32 (-0.10,0.74)	0.70 (-1.65,3.05)
$\widehat{\eta}$	0.57 (0.42,0.71)	0.43 (0.29,0.59)

Notes. Parameter estimates of means and mixing proportions (95% confidence intervals in brackets) by posterior means.

TABLE: 3: NUMBER OF COMPONENTS (SPECIFIC CHARACTERISTICS)

K	LogLik	AIC	BIC	EN	BIC-EN	Bayes factor (k=i/k=i+1)
1	-2812.87	5653.74	5701.38	0	5701.38	677.87
2	-2473.94	5007.87	5109.95	0.00	5109.95	1376.95
3	-1785.46	3660.92	3814.04	5.45	3824.93	317.47
4	-1626.73	3373.45	3577.61	15.81	3609.24	216.85
5	-1518.30	3186.60	3441.80	6.97	3455.74	19.43
6	-1508.58	3197.16	3503.40	5.78	3514.96	64.33
7	-1476.42	3162.84	3520.12	5.47	3531.06	133.01
8	-1409.91	3059.83	3468.15	11.46	3491.07	-

Notes. See notes of Table 1.

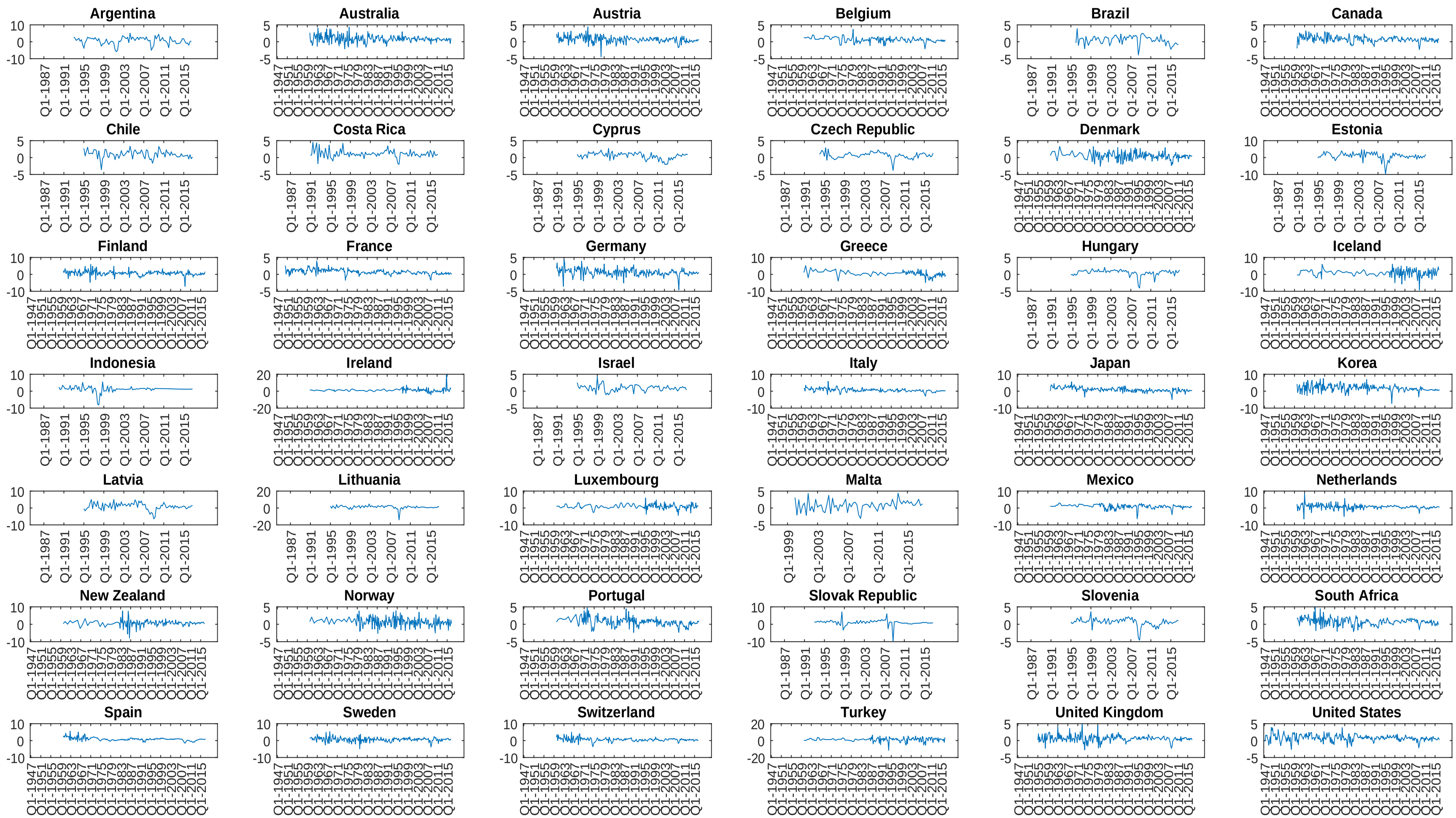
TABLE: 4: ESTIMATED PARAMETERS (SPECIFIC CHARACTERISTICS)

Parameter	Estimates		
	Group 1 (outliers)	Group 2 (big recessions)	Group 3 (normal recessions)
	Duration		
$\widehat{\mu}$	21.78 (13.8,34.79)	6.79 (6.07,7.55)	3.08 (2.90,3.27)
	Amplitude		
$\widehat{\mu}$	-28.36 (-40.62,-21.04)	-7.73 (-8.96,-6.43)	-2.11 (-2.32,-1.91)
	Cumulation		
$\widehat{\mu}$	-367.85 (-613.26,-216.47)	-28.82 (-34.28,-23.88)	-3.32 (-3.73,-2.88)
	Excess		
$\widehat{\mu}$	46.23 (0.40,74.38)	1.59 (-0.23,3.49)	-0.03 (-0.15,0.10)
$\widehat{\eta}$	0.03 (0.01,0.05)	0.30 (0.24,0.36)	0.68 (0.61,0.73)

Notes. See notes of Table 2.

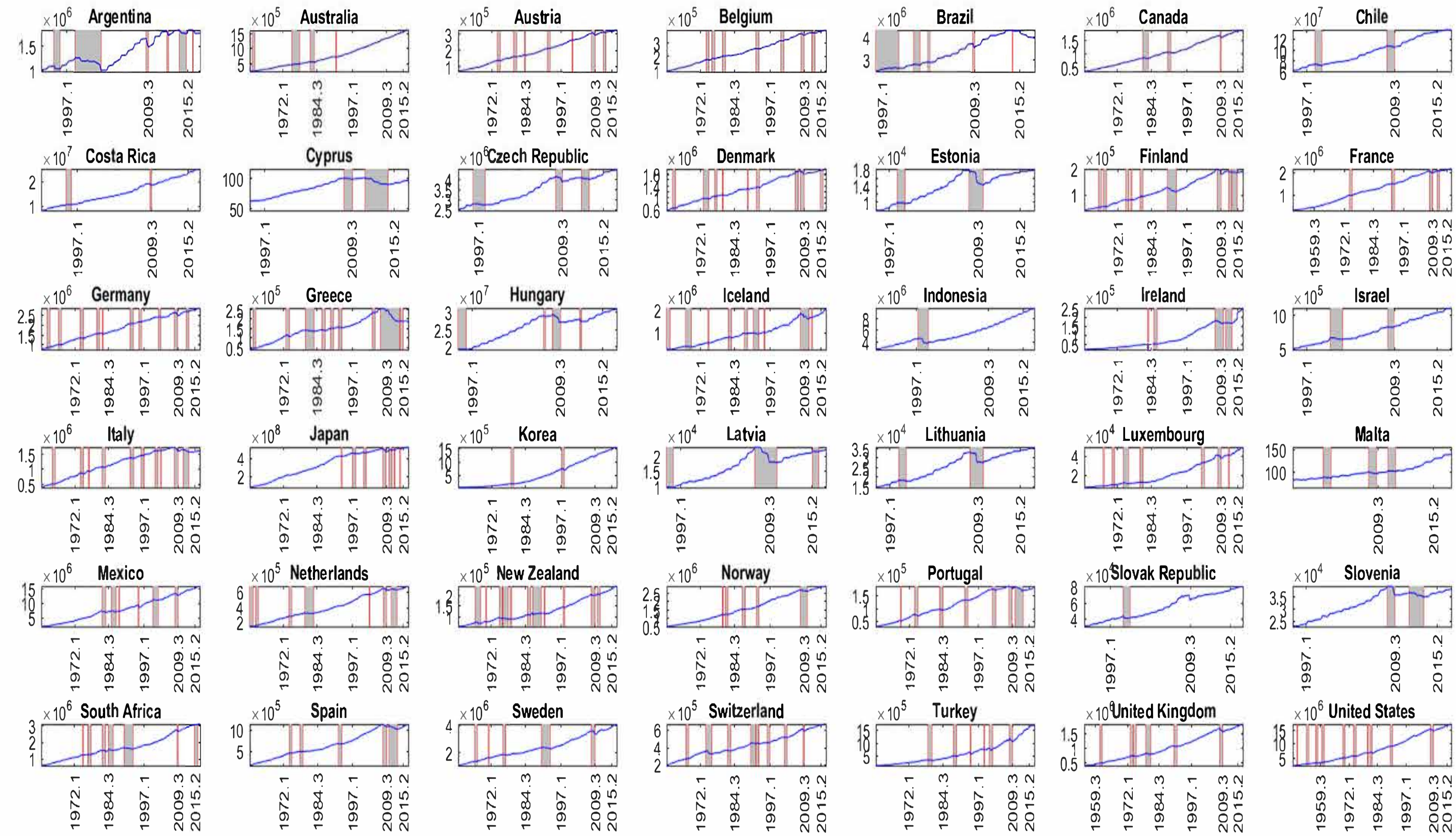
Figures

Figure: 1: Evolution of real GDP grpwth in OECD countries



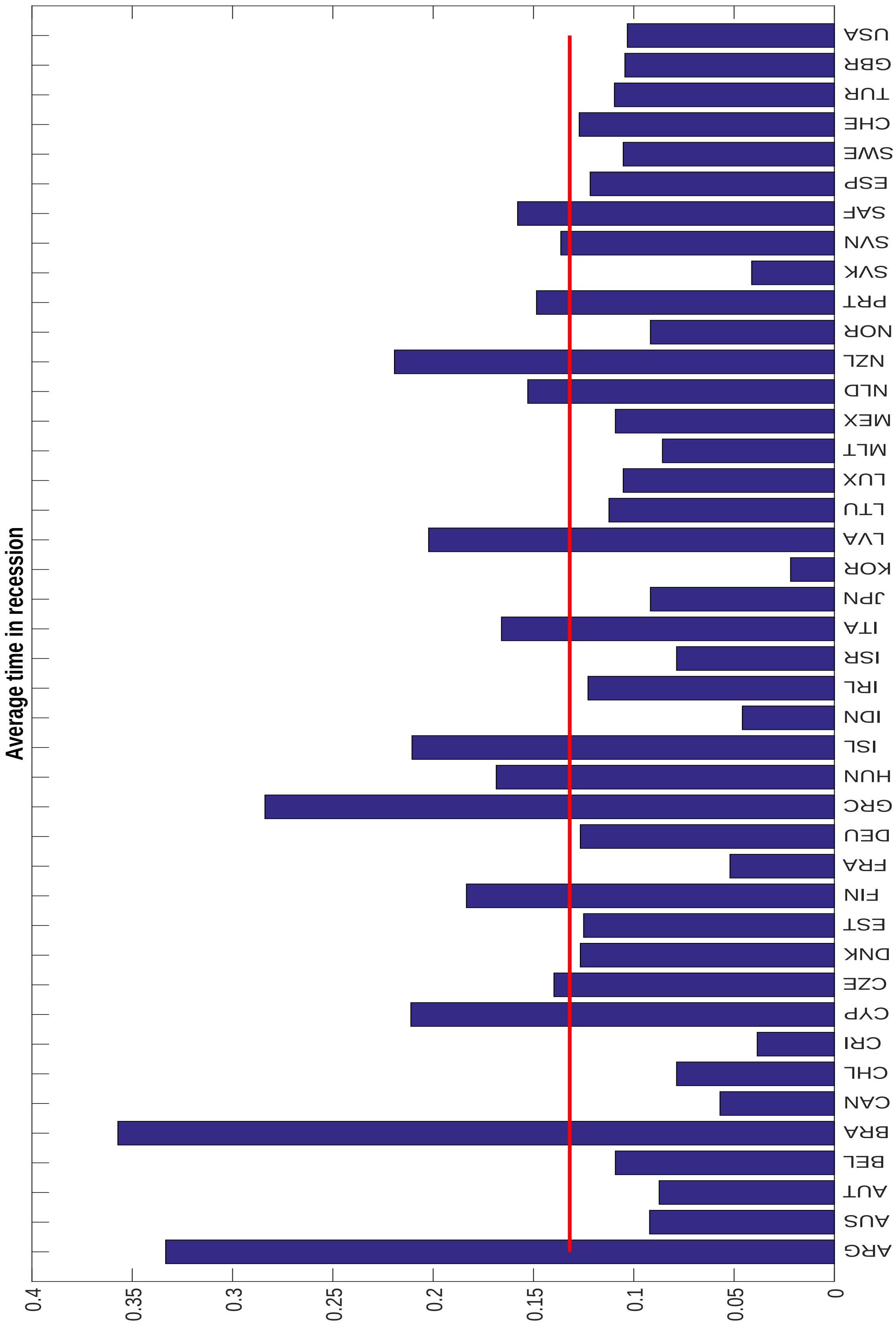
Notes. The figure shows the evolution of quarterly GDP growth for 42 OECD countries from 1947 to 2017.

Figure: 2: Business cycle in OECD countries



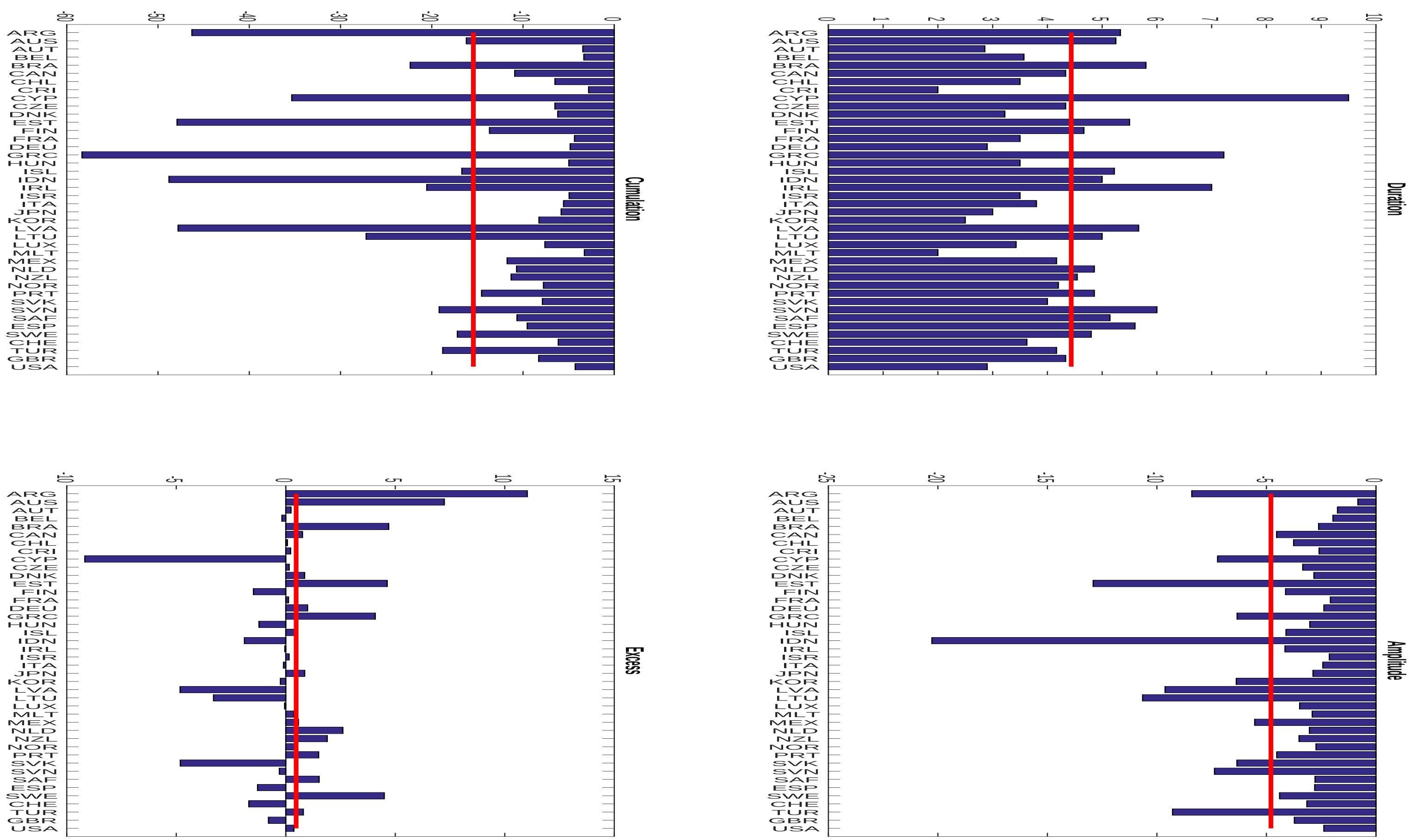
Notes. The figure shows the evolution of quarterly real GDP for 42 OECD countries from 1947 to 2017. The vertical lines refer to the Bry-Boschan turning points, while the recessions are identified by shaded areas.

Figure 3: Incidence of recessions in OECD countries



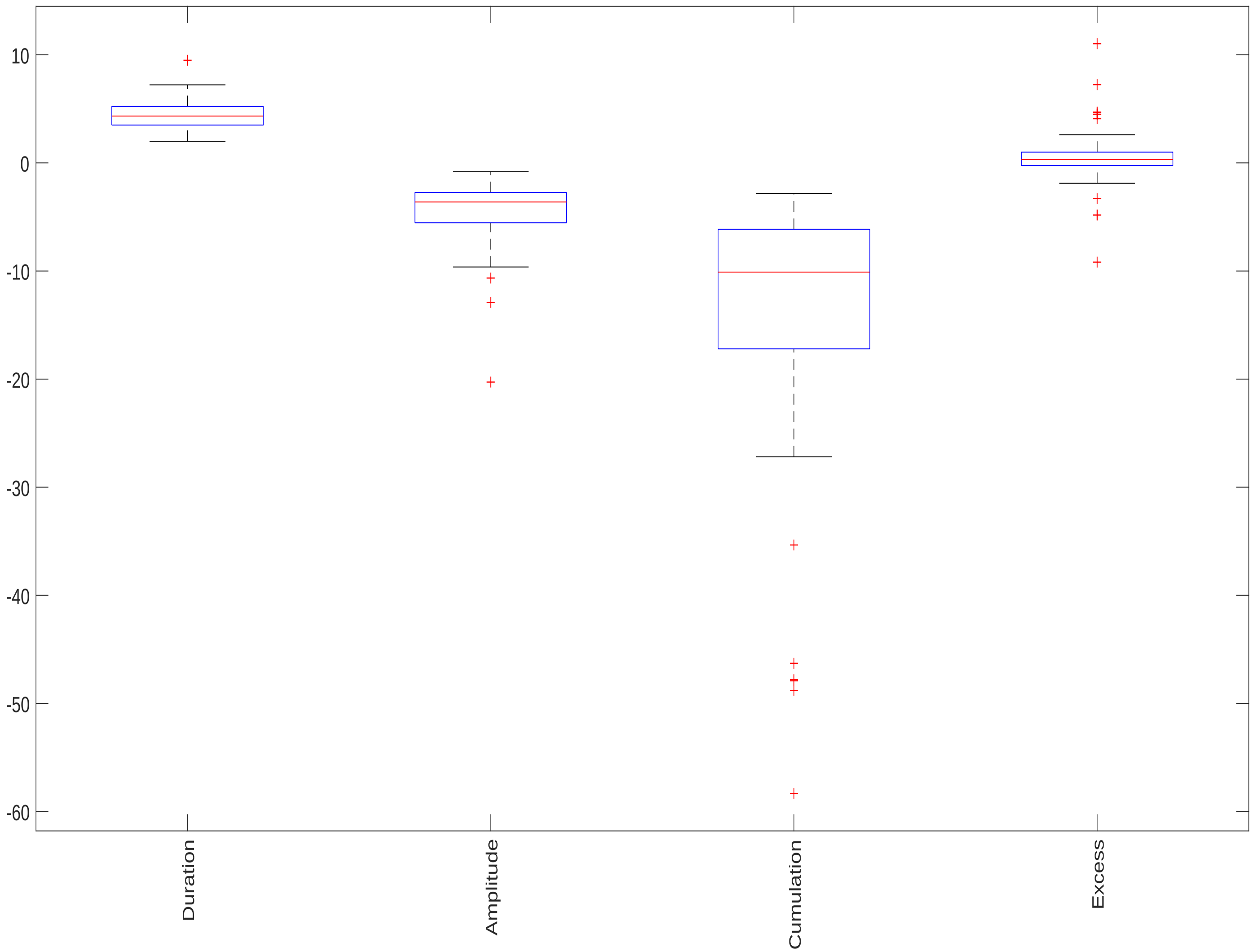
Notes. The figure shows the percentage of quarters that each country is in recession. The horizontal line refers to the averaged value.

Figure: 4: Recession characteristics in OECD countries



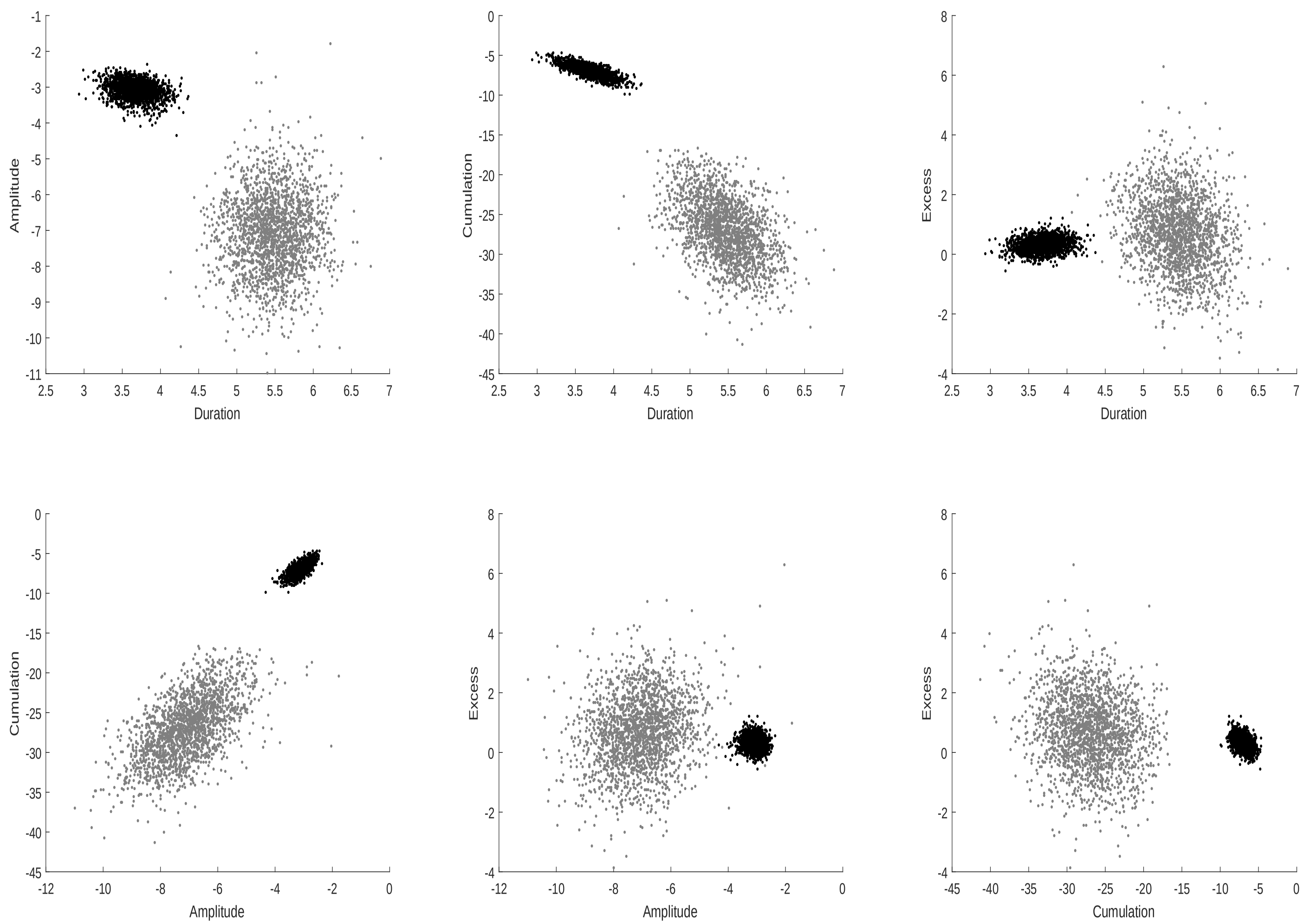
Notes. The panel show the averaged duration, amplitude, cumulation and excess for each country. The horizontal lines refer to the international averages.

Figure: 5: Boxplot of averaged recession characteristics



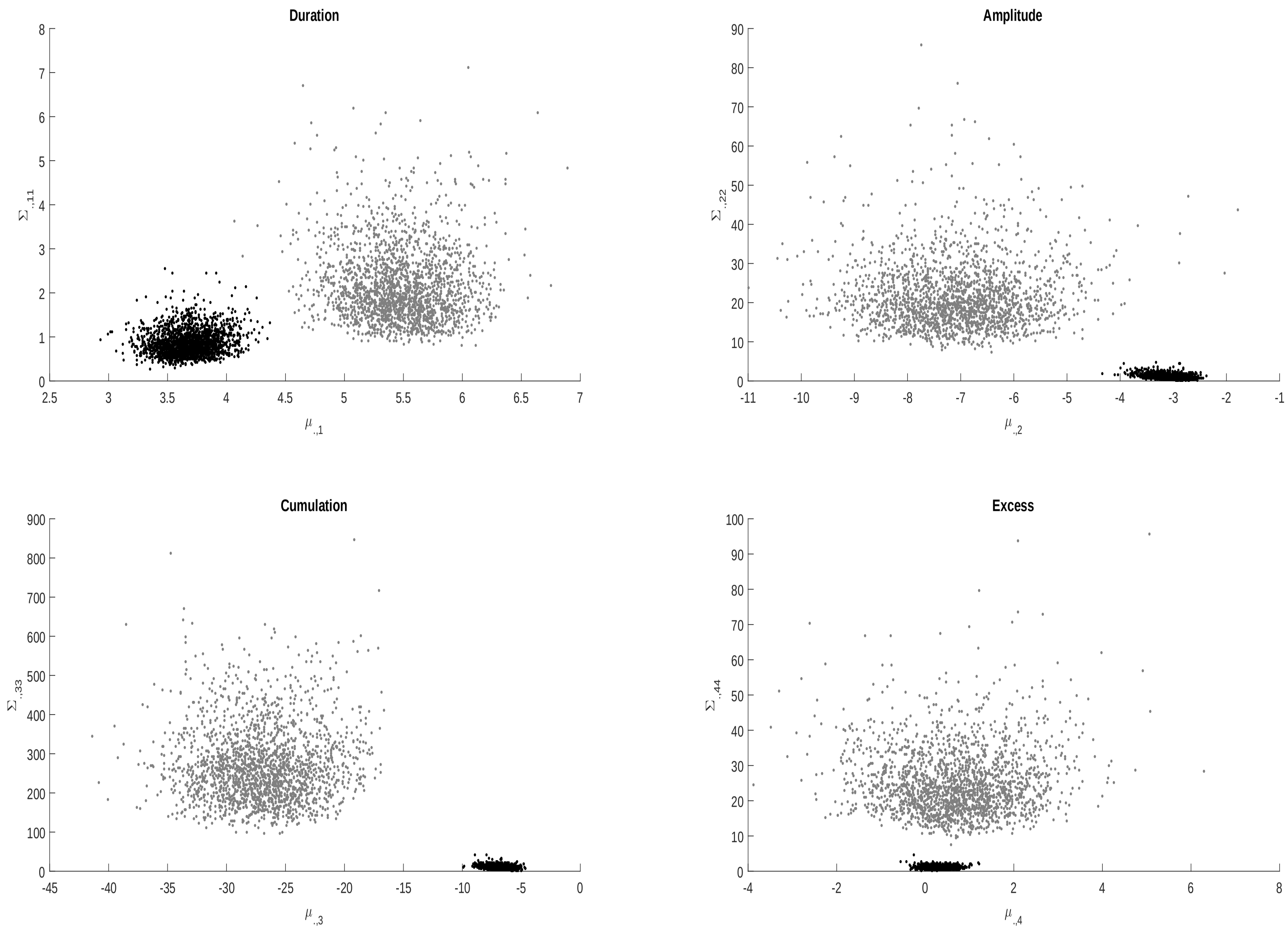
Notes. First and third quartiles appear at the bottom and top of the boxes, while the medians are plotted as horizontal line inside the boxes. Bottom and top horizontal lines outside the boxes are the minimum and maximum values, excluding outliers, which are plotted as crossed symbols.

Figure: 6: Draws of MCMC for μ, average of OECD countries



Notes. The figure displays the two-dimensional scatter plots of the MCMC draws for the means of each pair of characteristics.

FIGURE: 7: DRAWS OF MCMC FOR μ AND σ, AVERAGE OF OECD COUNTRIES

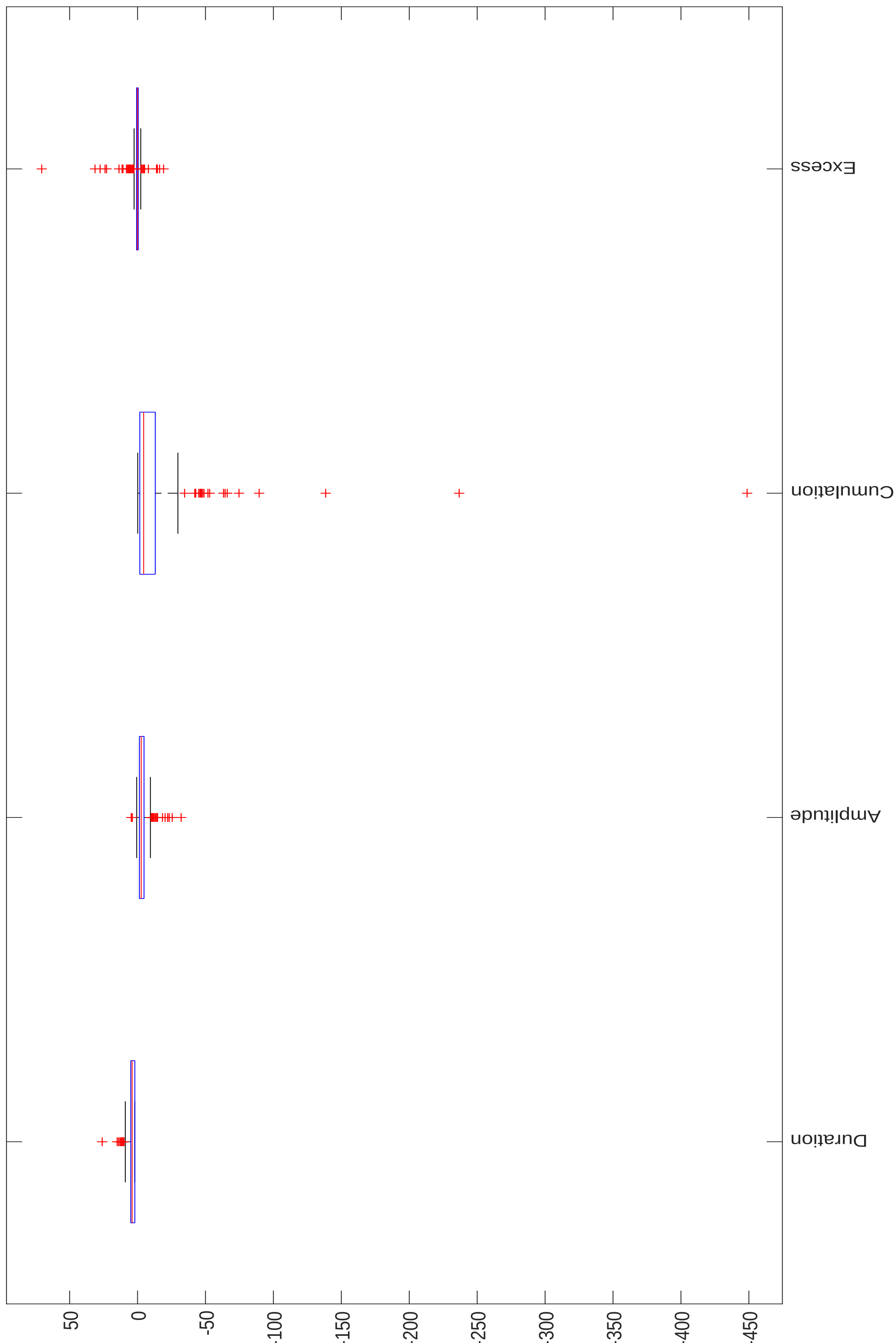


Notes. The figure displays the two-dimensional scatter plots of the MCMC draws for the means and variances of each characteristic.

Figure: 8: Geographical distribution of recessions of OECD countries

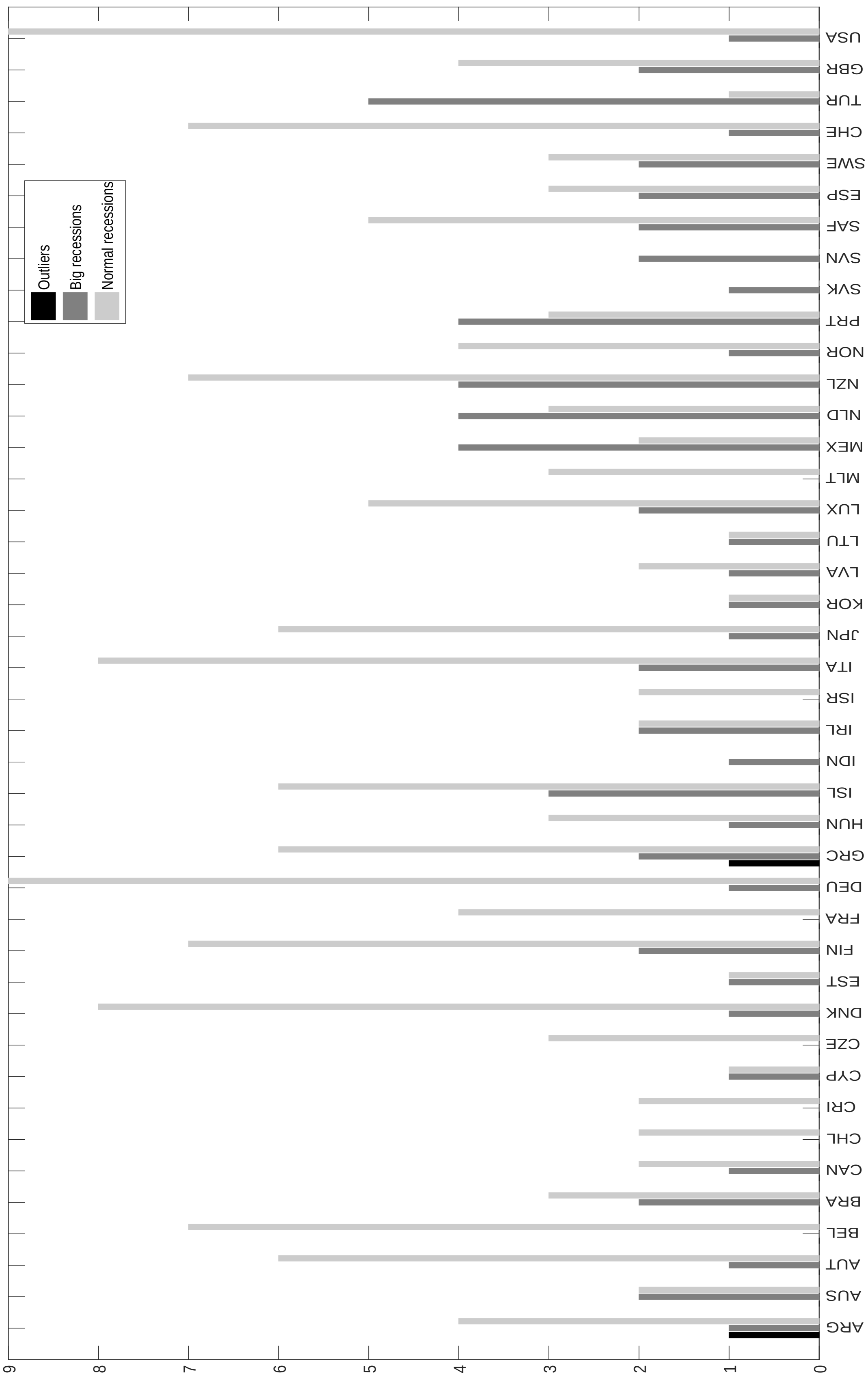
Notes. The figure sketches the geographical distribution of the two clusters. Dark grey countries belong to Group 1 (normal recessions and light grey countries belong to Group 2 (big recessions). Countries that do not belong to our sample appear in white.

Figure: 9: Boxplot of specific recession characteristics



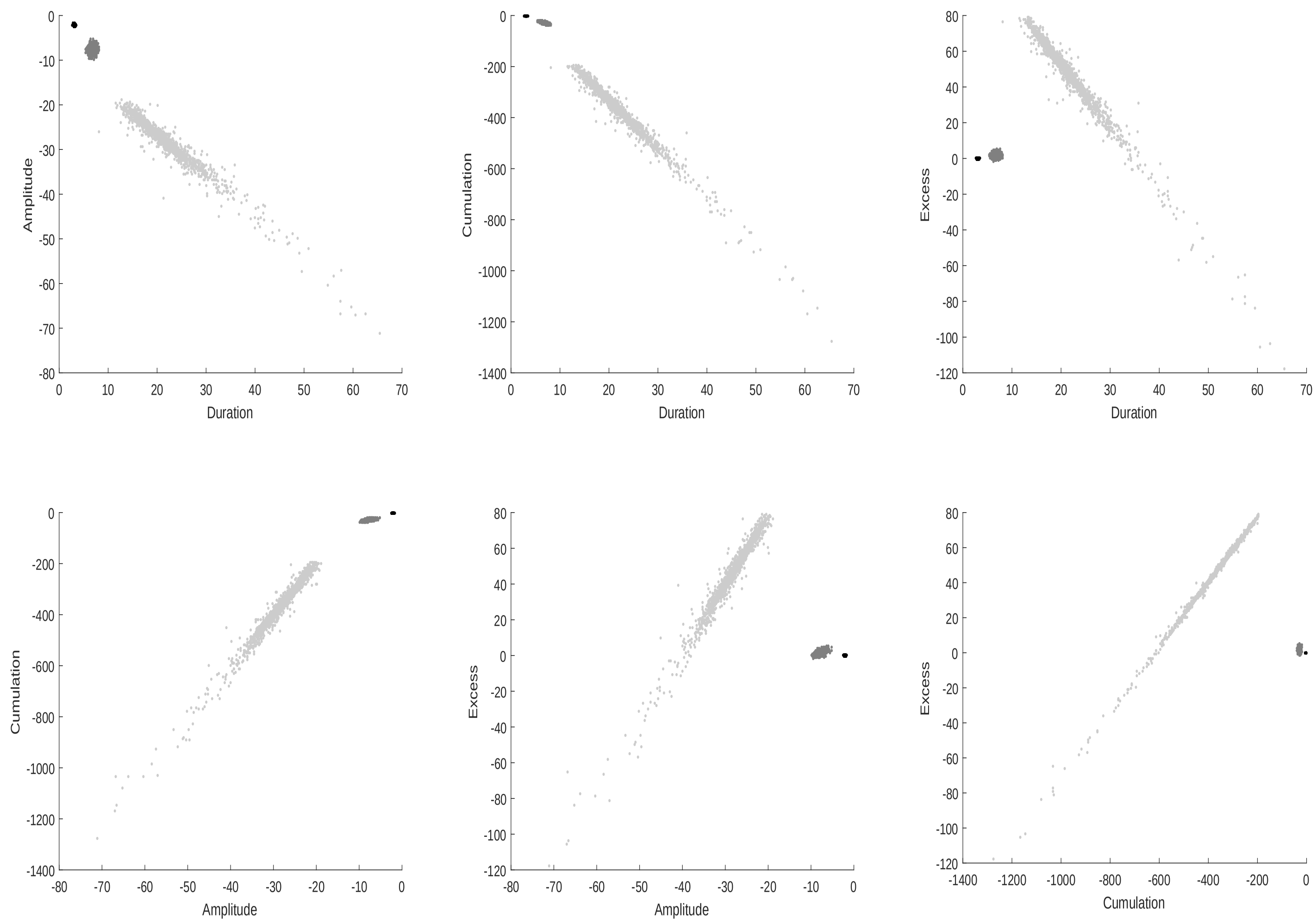
Notes. See notes of Figure 5.

Figure: 10: Clustering recessions of OECD countries



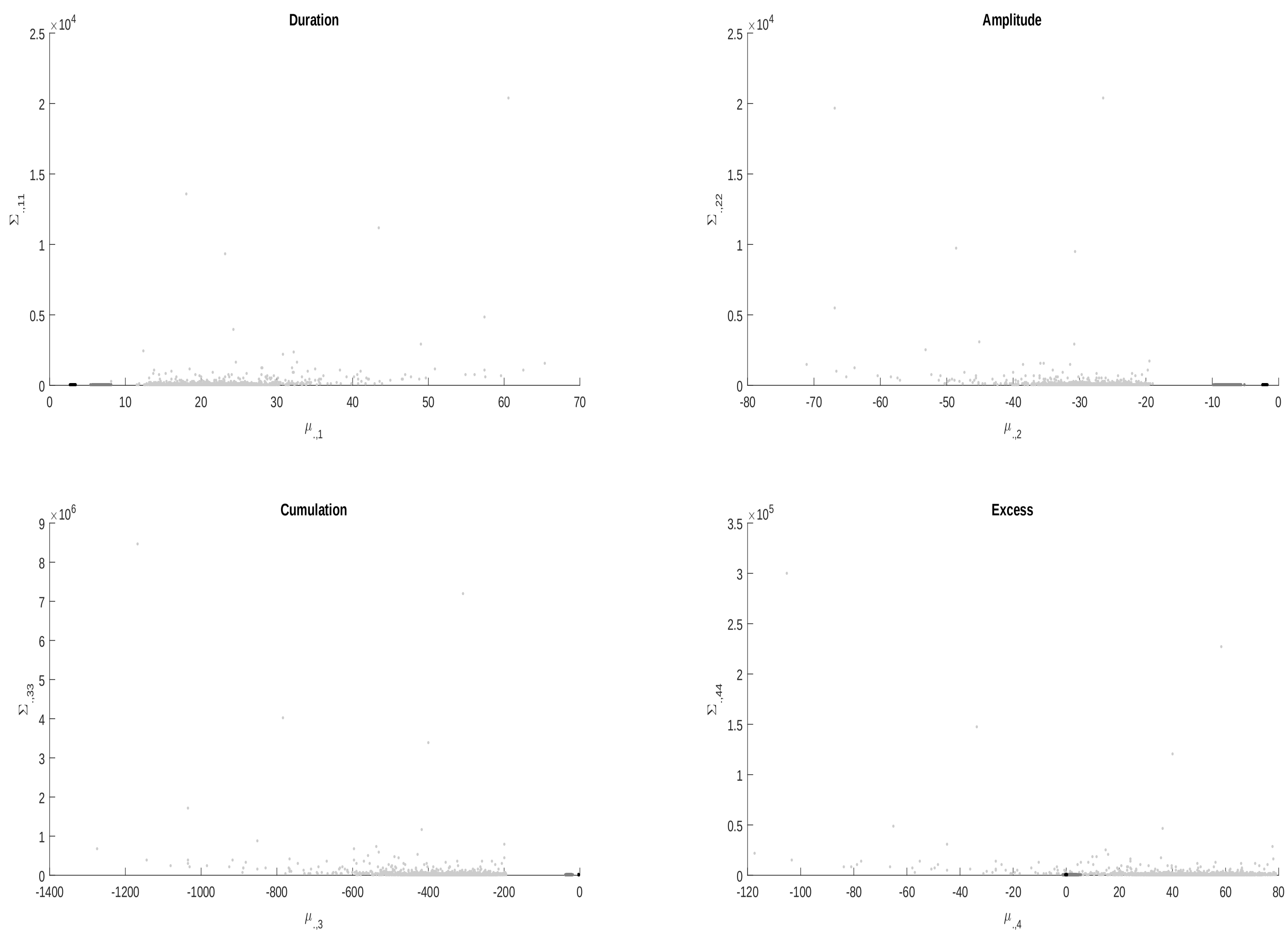
Notes. The figure displays the number of outliers (black bars), big recessions (dark grey bars), and normal recessions (light grey bars) of each country.

FIGURE: 11: DRAWS OF MCMC FOR μ, INDIVIDUAL RECESSIONS



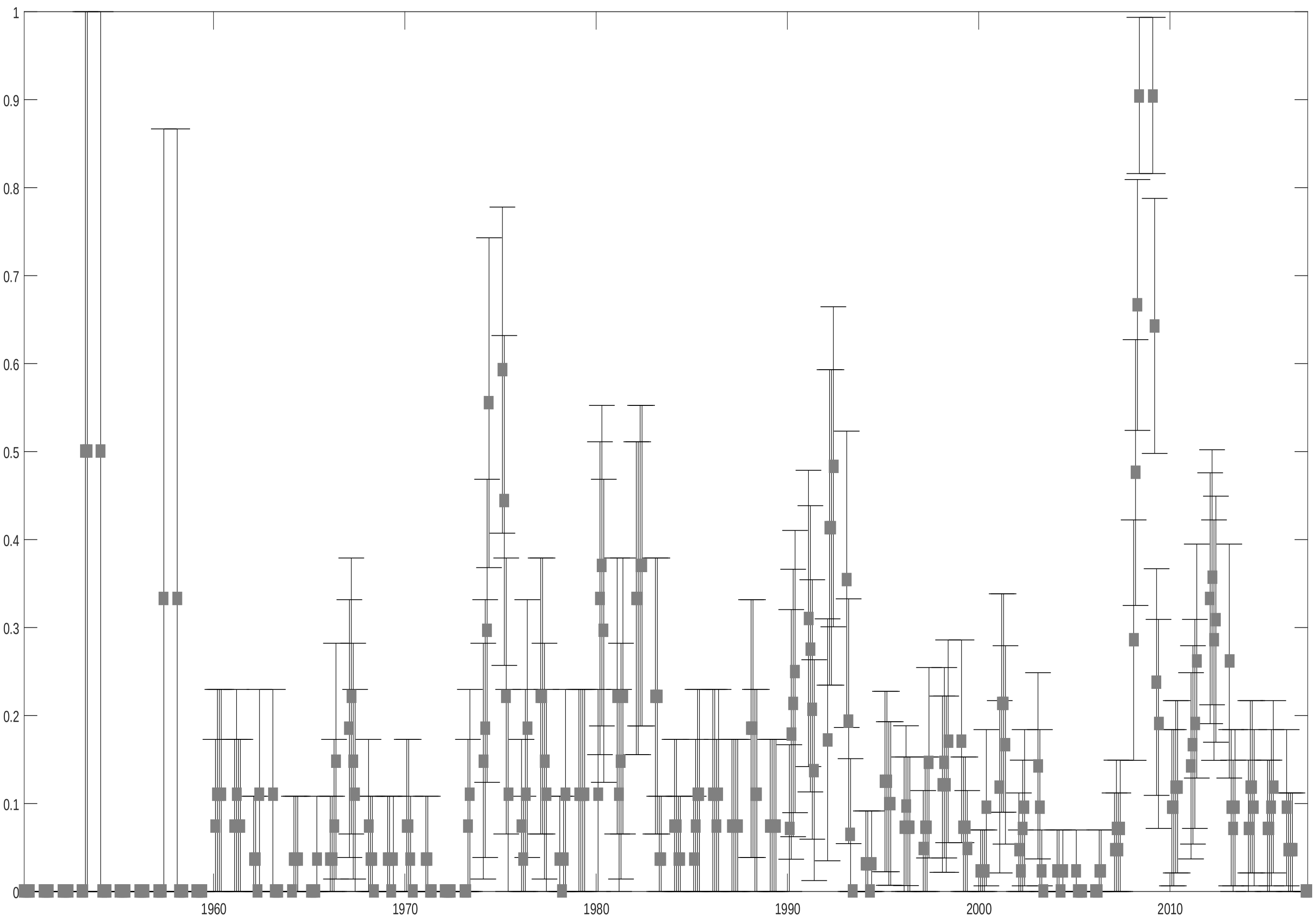
Notes. See notes of Figure 6.

FIGURE: 12: DRAWS OF MCMC FOR μ AND σ, INDIVIDUAL RECESSIONS



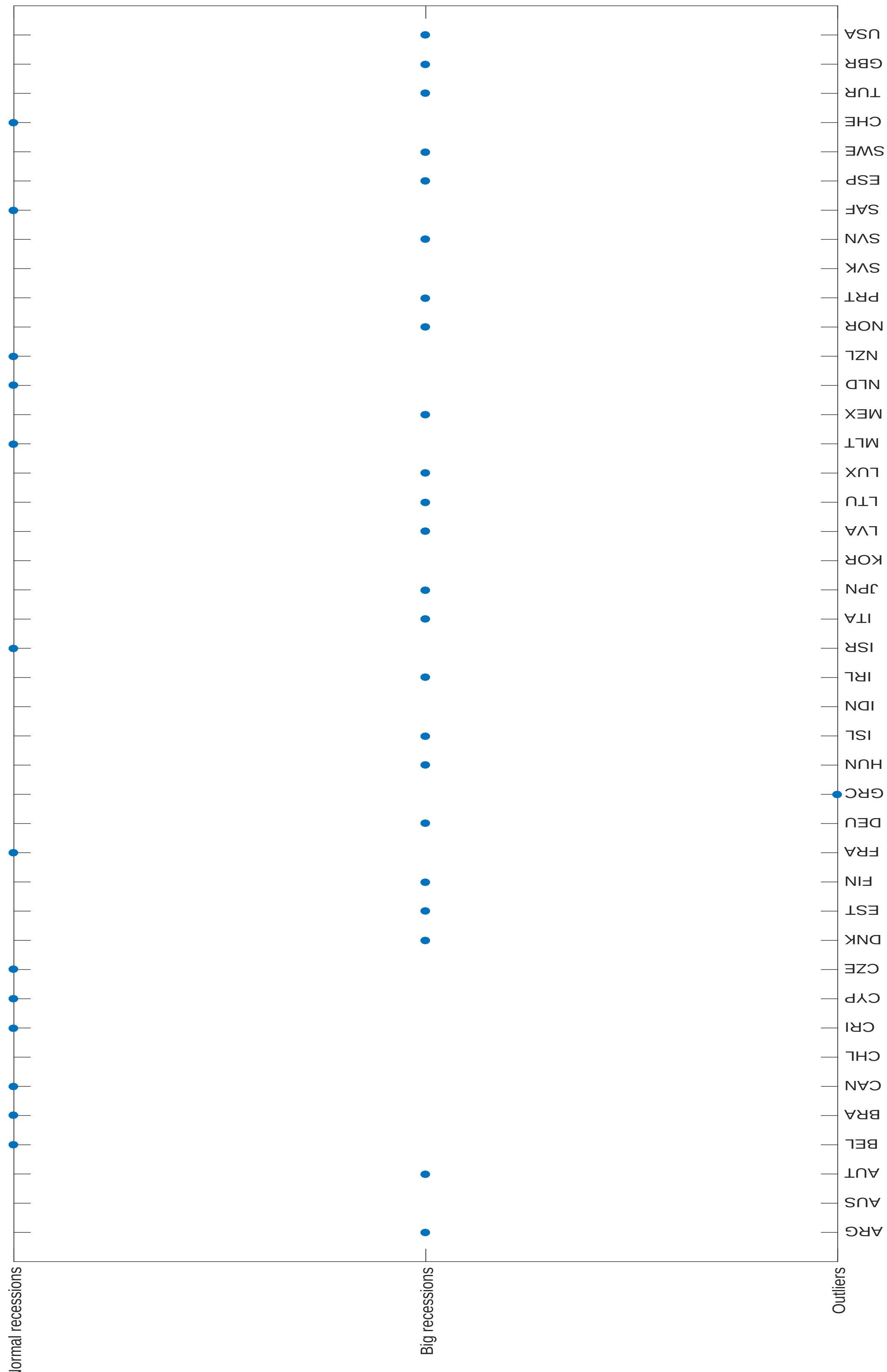
Notes. See notes of Figure 7.

Figure: 13: Index of recession synchronization in OECD countries



Notes. The figure displays the estimated probability that, according to the Bry-Boschan business cycle dating algorithm, all the countries are in recession in each quarter from 1947 to 2017. The 95% confidence intervals are plotted as black bars with whiskers.

Figure: 14: Position of GR in each cluster



Notes. The figure marks with shaded circles the classification of the Great Recession into the three groups for each country.