Persistence in the Banking Industry: Fractional integration and breaks in memory*

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Abstract

Certain "spurious long memory" processes mimic the behavior of fractional integration in that the variance of their sample mean behaves like that of a fractionally integrated process of some order $\mathcal{D}$. We show, however, experimentally that a fractional integration test may discriminate between spurious long memory of order $\mathcal{D}$ and integration of order $\mathcal{D}$. Further, we suggest a test for the null hypothesis that the order of integration does not change from one subperiod to another. It simply builds on the difference of the estimates from the respective subsamples that are split exogenously. Upon appropriate normalization a limiting standard normal distribution arises. With these methods we tackle the question whether international and sectoral bank equity index returns are fractionally integrated and whether the memory parameters have changed. The daily data are split into three regimes: one pre-crises subsample, a second including the collapse of the Lehman Brothers bank, and a third covering the Euro area sovereign debt crisis. In particular, we provide evidence that both turmoils had differing international effects.

Keywords: Spurious long memory; breaks in persistence; Lehman Brothers collapse; European sovereign debt
JEL: C22, G21, G32.

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1 Introduction

Ding, Granger and Engle (1993) documented the existence of long-range dependence in several transformations of the absolute value of daily returns, noting that these proxies of volatility exhibit autocorrelation functions characterized by a slow decay to zero. Granger and Ding (1996) found this form of persistence to be conformable with a fractionally integrated process (also known as long-memory process) with characteristic coefficient of around $\widehat{d} = 0.47$. This evidence has been extended to realized volatility measures, for which the estimates of the fractionally integrated parameter tend to lie around this value; see, for instance, Andersen, Bollerslev, Diebold and Labys (2003) and Hassler, Rodrigues and Rubia (2012). Nevertheless, the evidence of long-memory in volatility and other time series may arise spuriously from a number of considerations. Lobato and Savin (1998) addressed this issue analyzing whether the rejection of the hypothesis of short memory dynamics in squared and absolute returns may be attributed to "true long memory" or to other causes termed "spurious long memory" including, for instance, parameter instability. This topic has attracted considerable attention in the econometric literature; see, among others, Diebold and Inoue (2001), Granger and Hyung (2004), Smith (2005), Ohanissian, Russell and Tsay (2008), Perron and Qu (2010) and Qu (2011).[1] The recent literature on long-memory has focused on the stability of the long-memory coefficient, reporting evidence suggesting that the degree of persistence may vary over time; see Kumar and Okimoto (2007), Bos, Koopman and Ooms (2012), Martins and Rodrigues (2012) and Hassler and Meller (2014).

In this paper, we discuss several diagnostic tools to address the suitability of a fractionally integrated model with constant order of integration in the time-series context. We then implement these procedures on returns of representative stock portfolios of the banking industry in different regions and economic areas aiming to analyze whether the characteristic degree of persistence in the volatility of these series has remained stable or whether it has changed as a consequence of the global financial crisis. This issue, which is particularly relevant for both analysts and forecasters, has not been addressed in the extant literature. After the collapse of Lehman Brothers in 2008 and the subsequent shocks that featured the Great Recession and the European sovereign debt crisis, financial institutions worldwide have faced an extremely uncertain operating environment. Repeated rating downgrades, sharp regulatory changes, and widening funding-spreads have led to unprecedented levels of market volatility in the sector, particularly, in peripheral Europe. While it is perfectly clear that the mean of the volatility process shifted as a consequence of the financial crisis, it is possible that other characteristics of the data generating process, such as the degree of persistence, may have changed as well. Under extreme market circumstances, shocks on the variability of returns may become more persistent because investors become more risk-averse. As a result, the long-memory parameter that characterizes the long-term dynamics of the volatility process

[1] There is an older, related literature on the potential confusion of slowly varying trends and long memory, see e.g. Bhattacharya, Gupta and Waymire (1983), Künsch (1986), or Giraitis, Kokoszka and Leipus (2001).

of returns may take larger values and exhibit non-stationary features. The severity of the consequences on the banking industry provides us with the perfect ground to detect potential changes in the degree of persistence, bringing new evidence to the field.

To this end, we proceed as follows. We first analyze the resilience of the regression-based test proposed by Demetrescu, Kuzin and Hassler (2008) [DKH henceforth] to detect true long memory against a backdrop of spurious long memory. This test can exhibit more power than alternative procedures, while retaining a considerable degree of tractability and methodological simplicity. More specifically, we analyze the frequency of rejection of this test when the data generation process is driven by a variety of spurious long memory models that have been discussed in previous literature as well as a novel specification based on an unobserved components model proposed in this paper. Monte Carlo analysis shows that the DKH test has considerable power to reject spurious long memory in realistic settings. Additionally, we suggest a simple test for the null hypothesis that the memory estimates of two non-overlapping subsamples are equal, building on an approach discussed by Shimotsu (2006). The test statistic follows asymptotically a standard normal distribution. Finally, we use this testing procedure and the DKH test to characterize the persistence of the log transform of daily absolute returns of different bank equity indices over different periods. More specifically, we consider daily returns representative of different countries, regions and international areas (*e.g.,* the US, Asia and Southern Europe) and economic zones (*e.g.*, "Emerging Markets" or G7). Since our main interest lies in characterizing the effects on persistence of different episodes related to the recent financial crisis, we split the total sample into three disjoint periods: the first one being a period where banks have operated without major global events; the second one containing the global financial crisis following the collapse of the Lehman Brothers bank in September 2008; and the third one including the Euro area sovereign debt crisis starting in early 2010.

We provide confidence intervals for the order of integration based on the DKH procedure by inverting the range of values not rejected by the integration test. We also report point estimates using semiparametric procedures and their corresponding confidence intervals and analyze the difference over the subperiods. The overall evidence from this analysis suggests the existence of true long memory dynamics driving the volatility of these series. The suitability of a model with constant parameter over the total period is generally rejected, showing that shocks in volatility tend to be more persistent during the turmoil period. Although a common picture emerges, there are important differences among the different countries, regions and economic areas considered. The effects of the crisis were more pronounced in areas with direct exposure. This evidence is consistent with the hypothesis that long-range persistence may be linked to economic fundamentals.

The rest of the paper is organized as follows. Section 2 introduces the standard notation of true fractionally integrated series and becomes precise on the class of models featuring spurious long memory of a certain degree denoted as $\mathcal{D}$ throughout the paper. Some prominent examples are discussed. In Section 3 we report Monte Carlo evidence on how well the

DKH procedure discriminates between spurious long memory of degree $\mathcal{D}$ and fractional integration of the same order. In Section 4, we briefly introduce and discuss the test for the null hypothesis that non-overlapping subsamples are integrated of the same order, while Section 5 contains the results of our empirical analysis. The final section summarizes our main findings.

2 Notation and definitions

We start our analysis by introducing notation, the formal definition of (true) long memory analyzed in this paper, and the statistical implications of the class of fractionally integrated models. We then discuss alternative specifications that give rise to spurious long memory within a class of shift-in-mean models. All these specifications will be used in the Monte Carlo section to address the resilience of the DKH test.

2.1 True vs. spurious long memory

By true long memory we understand fractional integration of positive order d. Generally, let $\{y_t\}$, $t = 1, ..., T$, denote a stationary fractionally integrated process with parameter $-1/2 < d < 1/2$, in short $I(d)$. It is defined by

$$y_t = \mu + (1 - L)^{-d} x_t \,, \quad (1 - L)^{-d} = \sum_{j=0}^{\infty} \binom{-d}{j} (-L)^j \tag{1}$$

where $\mu < \infty$ is the expected value of the process, L is the standard lag operator, $L^j x_t = x_{t-j}$, and $\{x_t\}$ is a covariance stationary process whose spectral density is bounded and bounded away from zero at the origin. The distinctive feature of fractionally integrated models is that the coefficient d is allowed to take on non-integer values. When $\{x_t\}$ verifies suitable conditions, $\{y_t\}$ admits the Wold decomposition $y_t = \mu + \sum_{j=0}^{\infty} \psi_j(d) \varepsilon_{t-j}$ with impulse response coefficients $\{\psi_j(d)\}$ dying out hyperbolically at rate j^{d-1}; a necessary and sufficient condition on $\{x_t\}$ for such a behaviour to hold has been given by Hassler and Kokoszka (2010, Prop. 2.1). For $d < 0.5$, the sequence $\{\psi_j(d)\}_{j \geq 0}$ is square summable and, therefore, $\{y_t\}$ is a stationary process. Nevertheless, the sequence is not absolutely summable when $d > 0$, which gives rise to an impulse response sequence characterized by long memory. The larger the order of integration d, the slower $\psi_j(d)$ dies out, such that d measures the degree of memory (persistence) in the process. The long-term dependence just defined is reflected by long memory in the autocorrelogram. The autocovariances $\gamma(h)$ of $\{y_t\}$ vanish at rate h^{2d-1} for a growing lag h, such that the correlation dies out more slowly the larger the values of d are, $0 < d < 0.5$, and this behaviour translates into a pole at the origin of the spectral density f in the frequency domain, $f(\lambda) \sim G \lambda^{-2d}$, $\lambda \to 0$, where G is a finite, strictly positive constant; see Palma (2007, Theo. 3.1) or Hassler and Kokoszka (2010, Coro. 2.1). Those characteristics of fractional integration have also been coined "true long memory"; see Lobato and Savin (1998). Finally, fractional integration also characterizes how fast the variance of the sample mean converges. As shown by Samarov and Taqqu (1988) and Yajima (1989), it follows as $T \to \infty$ that

$$Var\left(\sum_{t=1}^{T} y_t\right) = O(T^{2d+1})\,, \qquad |d| < 0.5, \tag{2}$$

while the nonstationary case is trivially covered by a corresponding result in differences:

$$Var\left(\sum_{t=2}^{T} \Delta y_t\right) = O(T^{2d-1}), \quad 0.5 < d < 1.5. \tag{3}$$

The econometric literature has discussed a number of alternative models to (1) in which the variance of the sample mean displays the same characteristic behavior as a fractionally integrated model, but without necessarily imposing stationarity and, therefore, without having well-defined autocorrelations or spectral densities. Consequently, these processes are said to exhibit spurious long memory, and standard estimation procedures may be biased to find significant values of long-memory estimates. Most of these models are based on mean shifts.[2]

We first discuss a general data generating process (DGP) that accommodates the possibility of shifts in mean. Particular cases nested in this category will be presented in the following subsection. To this end, consider a time-varying mean function $\{\mu_t\}$ superimposed by some white noise process $\{\varepsilon_t\}$, such that the observable process $\{z_t\}$ is generated as

$$z_t = \mu_t + \varepsilon_t\,, \quad \varepsilon_t \sim iid(0, \sigma_\varepsilon^2). \tag{4}$$

For a suitable choice of the DGP of $\{\mu_t\}$, it follows that, paralleling (2) and (3),

$$Var\left(\sum_{t=1}^{T} z_t\right) = O(T^{2\mathcal{D}+1}) \text{ or } Var\left(\sum_{t=2}^{T} \Delta z_t\right) = O(T^{2\mathcal{D}-1}) \tag{5}$$

where the value of $\mathcal{D}$ depends on specific assumptions that control $\{\mu_t\}$. Because $\{z_t\}$ mimics some of the characteristics exhibited by a fractionally integrated process of order $\mathcal{D}$ and, hence, could be spuriously identified as an $I\left(\mathcal{D}\right)$ process, $\{z_t\}$ is said to display spurious long memory.

Before introducing more specific examples, it is interesting to relate (5) to the concept of summability of order $\mathcal{D}$ recently introduced by Berenguer-Rico and Gonzalo (2014), which is verified by a series $\{z_t\}$ if

$$\frac{\mathcal{L}(T)}{T^{\mathcal{D}+1/2}} \sum_{t=1}^{T} (z_t - m_t) = O_p(1) \tag{6}$$

for some deterministic sequence $\{m_t\}$, a slowly varying function $\mathcal{L}(T)$, and the minimum number $\mathcal{D}$, such that the left-hand side is bounded in probability. Note that, if $E(z_t) = 0$ with $Var\left(\sum_{t=1}^{T} z_t\right) = O(T^{2\mathcal{D}+1})$ and $\mathcal{D} > -0.5$, then z_t is summable of order $\mathcal{D}$ by the

[2] The first paper we are aware of that addressed the potential confusion of long memory and mean shifts is by Klemeš (1974, p. 675): "*It is shown that the Hurst phenomenon is not necessarily an indicator of infinite memory of a process. It can also be caused by nonstationarity in the mean.*"

Chebyshev inequality. Moreover, summability of order $\mathcal{D}$ is closely related to the so-called Hurst coefficient H with $H = \mathcal{D} + 0.5$, which is defined if the normalized range

$$\frac{1}{T^H}\left\{\max_{1\le t\le T}\sum_{j=1}^{t}(z_j-\overline{z})-\min_{1\le t\le T}\sum_{j=1}^{t}(z_j-\overline{z})\right\} \tag{7}$$

converges as $T \to \infty$; see, for instance, Bhattacharya *et al.* (1983).

2.2 Occasional mean shifts

We now turn to four special cases of (4) allowing for occasional breaks in the mean.

A) Random level shift model

Following Chen and Tiao (1990), Granger and Hyung (2004) consider a model with random level shifts characterized by

$$\mu_t = \mu_{t-1} + q_t\,\eta_t = \mu_0 + \sum_{i=1}^{t} q_i\,\eta_i\,, \tag{8}$$

where $\{q_t\}$ is an iid sequence following a binomial distribution with probability $p \in (0,1)$, namely,

$$\Pr(q_t = x) = p^x(1-p)^{1-x}\,,\quad x \in \{0,1\}\,.$$

For the independent iid sequences $\{q_t\}$, $\{\eta_t\}$ and $\{\varepsilon_t\}$ satisfying zero starting value conditions, Granger and Hyung (2004) show that for a fixed probability $p > 0$

$$Var(z_T) = Var\left(\sum_{t=2}^{T}\Delta z_t\right) = O(T)\,, \tag{9}$$

such that $\mathcal{D} = 1$ in terms of (5) and, that therefore, the process is likely to be confused with an integrated process of order 1.

B) Markov switching mean function

Diebold and Inoue (2001) propose a Markov-switching model to generate infrequent mean shifts. They assumed two latent states $s_t \in \{0,1\}$ independent of $\{\varepsilon_t\}$ with constant transition matrix characterized by the probabilities $p_{ij} := \Pr(s_t = j\,|\,s_{t-1} = i)$ which determine the mean process, *i.e.*,

$$\mu_t = \mu_0\,(1-s_t) + \mu_1\,s_t\,, \tag{10}$$

with constant mean values μ_0 and μ_1. Given a parameter $0 < \delta < 1$, Diebold and Inoue (2001) assume local-to-zero transition probabilities characterized by

$$p_{11,T}\,(\delta) = 1 - c_1\,T^{-\delta}\,,\quad p_{00,T}\,(\delta) = 1 - c_0\,T^{-\delta} \tag{11}$$

with $0 < c_0\,,\, c_1 < 1$. Then, it holds as $T \to \infty$ (see Diebold and Inoue, 2001, Prop. 3) that

$$Var\left(\sum_{t=1}^{T} z_t\right) = O(T^{\delta+1})\,, \tag{12}$$

and, therefore, the process $\{z_t\}$ behaves like an $I(\delta/2)$ process in terms of the variance of the cumulation. Note that the larger δ, the closer the probabilities $p_{ii,T}(\delta)\,,\ i = 0, 1$, are to one and, hence, shifts occur more rarely resulting in a more persistent appearance of $\{z_t\}$.

C) Stopbreak process

Diebold and Inoue (2001) also introduced a modification of the so-called stochastic permanent break or Stopbreak model, proposed by Engle and Smith (1999). The original model, characterized by

$$\mu_t = \mu_{t-1} + q_{t-1}(\gamma)\,\eta_{t-1} = \mu_0 + \sum_{i=1}^{t} q_{t-i}\,(\gamma)\,\eta_{t-i}\,, \tag{13}$$

with

$$q_{t-1}(\gamma) = \frac{\eta_{t-1}^2}{\gamma + \eta_{t-1}^2} \tag{14}$$

is non-decreasing in $|\eta_{t-1}|$ for positive values of the parameter γ. Diebold and Inoue (2001) modified this setting replacing γ by $\gamma_T(\delta)$, where

$$\gamma_T(\delta) = O(T^{\delta})\,, \quad \delta > 0\,, \tag{15}$$

such that $\gamma_T(\delta) \to \infty$ as T diverges. Under some restrictions (Diebold and Inoue, 2001, Prop. 2) show that

$$Var\left(\sum_{t=2}^{T} \Delta z_t\right) = O(T^{1-2\delta}) \tag{16}$$

such that the process $\{\Delta z_t\}$ from (4) with (13) behaves like an $I(-\delta)$ process. Therefore, $\{z_t\}$ may be confused with an $I(1-\delta)$ process. The standard Stopbreak model ($\delta = 0\,,\ \gamma_T(\delta) = \gamma$) corresponds to $z_t \sim I(1)$. Generally, the larger δ, the smaller q_{t-1}, the more stable μ_t and the less persistent $\{z_t\}$ is.

D) Unobserved components model

Finally, we consider a classical unobserved components [UC henceforth] model. The simplest specification in this class consists of a random walk component, $\mu_t = \sum_{j=1}^{t} \eta_j$, superimposed by additive noise, also known as local level models; see Harvey (1989). However, as T increases, the nonstationary random walk dominates the noise component and, hence, the UC model behaves asymptotically as an $I(1)$ process; see also Hassler and Kuzin (2009) and Stock and Watson (2007). We therefore introduce a suitable variant where the random walk component is dampened as its variance increases. In particular, we introduce a time-varying mean as a function of the parameters $\lambda > 0$ and $0 \leq \delta \leq 1$ such that

$$\mu_t = \frac{\lambda}{t^{1-\delta}} \sum_{j=1}^{t} \eta_j\,, \tag{17}$$

where $\{\eta_t\}$ is $iid(0,1)$ independent of $\{\varepsilon_t\}$. Note that δ controls the weight that is attached to the random walk component in this specification. For $\delta = 1$, the standard random walk plus noise model (UC with constant variance) is embedded in (17). It is straightforward to establish that

$$Var\left(\sum_{t=2}^{T} \Delta z_t\right) = O(T^{2\delta-1})\,. \tag{18}$$

According to the terminology in Berenguer-Rico and Gonzalo (2014), $\{\Delta z_t\}$ is hence summable of order $\delta - 1$, and the process $\{z_t\}$ from (4) with (17) mimics $I(\delta)$ behaviour: The larger δ, the bigger is the random walk component and the more persistent $\{z_t\}$ is.

3 Monte Carlo analysis

Much of the existing literature dealing with the effects of spurious long memory has focused on the probability of rejecting the null hypothesis of either $d = 0$ or $d = 1$ when the data is driven by spurious long memory according to (4). These papers typically studied the behavior of the so-called log-periodogram regression; see Diebold and Inoue (2001) for comprehensive Monte Carlo evidence, and Granger and Hyung (2004), Smith (2005) and Perron and Qu (2010) for asymptotic results. In this paper, we adopt a different perspective and address the probability of rejecting a model of fractional integration when the data are generated according to a spurious long memory model. In particular, we test the null hypothesis that the observable series is integrated of order $\mathcal{D}$ when the DGP is summable of order $\mathcal{D}$ satisfying (5), given the different models introduced in the previous section. In that sense, the analysis is confined to the least favorable case for a test aiming at the detection of true long memory. Second, we do not build on the log-periodogram regression to perform the tests, but rather apply a more powerful test rooted in the Lagrange Multiplier principle, namely, the regression-based fractional integration test advocated by Breitung and Hassler (2002) and Demetrescu, Kuzin and Hassler (2008). This analysis builds explicitly on the definition of long memory: When fractionally differencing the data one obtains a series that is integrated of order zero. This null hypothesis is tested in a regression framework of the data differenced under the null.

The main characteristics of the DKH test are briefly described in the sequel. The procedure assumes that the data are generated from (1) given some (unknown) value d_0 and a fairly general class of innovations $\{x_t\}$. The null hypothesis to be tested is that the order of integration of $\{y_t\}$ equals d_0, *i.e.*, $\mathrm{H}_0 : d = d_0$. For simplicity, we assume $\mu = 0$. In this case, one computes the differences under H_0:

$$x_{t,d_0} = (1 - L)^{d_0}\, y_t\,, \tag{19}$$

and defines the process

$$x^*_{t-1,d_0} = \sum_{j=1}^{t-1} j^{-1} x_{t-j,d_0}\,,\ t = 2, ..., T\,, \tag{20}$$

to run the auxiliary lag-augmented regression

$$x_{t,d_0} = \phi x^*_{t-1,d_0} + \sum_{j=1}^{k} a_j x_{t-j,d_0} + v_t,\ t = k+1, \ldots, T\,, \tag{21}$$

where the lag length k can be selected deterministically[3] as $k = \left[4\,(T/100)^{0.25}\right]$. Under the null hypothesis and weak regularity conditions, the squared t-statistics on $\phi = 0$ from this regression, namely t^2_ϕ, follows a χ^2 distribution with one degree of freedom, and H_0 is rejected for large values of this statistic. Alternatively, Demetrescu, Kuzin and Hassler (2008) recommended the use of White standard errors in order to robustify against conditional heteroskedasticity. Indeed, Kew and Harris (2009) showed that White standard errors guarantee valid asymptotic inference even under unconditional heteroskedasticity of very general form. We shall denote the resulting test statistic as $\widetilde{t}^2_\phi$ and compute both t^2_ϕ and $\widetilde{t}^2_\phi$ in the Monte Carlo analysis.

We simulate data $\{z_t\}$, $t = 1, ..., T$, $T \in \{250, 500, 1000\}$, according to the different specifications in A) to D) embedded in the DGP (4). Recall that none of these specifications is in general a fractionally integrated model, but they are summable of order $\mathcal{D}$, with this coefficient taking values depending on the specific model considered. The precise parameter configuration that defines $\mathcal{D}$ in any case will be detailed below. We test the null hypothesis $H_0 : d = \mathcal{D}$, computing $x_{t,\mathcal{D}} = (1-L)^{\mathcal{D}}\, z_t$ and $x^*_{t-1,\mathcal{D}}$, and running the auxiliary regression (21) to determine the test statistics t^2_ϕ and $\widetilde{t}^2_\phi$. We report the rejection frequency of the tests at a 5% nominal level based on 2,000 Monte Carlo replications.

A) Random level shift model.

We begin with the simple random level shift model in (8). The main parameter of interest is the probability, p, that controls the occurrence of a shift. For conciseness, we report the frequency of rejections for the set of probabilities p ranging from 0.01 up to 0.20. The results are reported in Table 1. For fixed T the power is decreasing with growing p, which is not surprising, since $p \to 1$ covers the random walk case. For fixed p the power is not monotonous in T (unless $p \leq 0.02$ for our fairly small sample sizes), which is clear asymptotically: For fixed p the result in (9) holds, such that the process behaves like $I(1)$ with growing T. To get a limiting behavior different from $I(1)$, p has to vanish with the sample size such that $pT \to \kappa$ for some $0 < \kappa < \infty$. In this case, limiting theory for autocorrelations is covered by Granger and Hyung (2004, Prop. 1) and Perron and Qu (2010, Prop. 1).

[3] See also Demetrescu, Hassler, Kuzin (2011) for a more detailed exposition on the issue of lag length selection.

Table 1: Random level shifts from (8)

	T=250		T=500		T=1000	
p	t_{ϕ}^{2}	$\widetilde{t}_{\phi}^{2}$	t_{ϕ}^{2}	$\widetilde{t}_{\phi}^{2}$	t_{ϕ}^{2}	$\widetilde{t}_{\phi}^{2}$
0.20	11.60	12.85	16.60	17.55	8.70	8.65
0.10	34.05	35.70	55.85	56.60	32.60	33.25
0.09	38.70	40.85	61.50	62.65	38.90	39.35
0.08	44.75	46.60	69.40	70.10	46.80	47.40
0.07	52.60	54.10	76.20	76.35	56.05	56.55
0.06	60.25	61.30	82.00	82.10	67.45	67.60
0.05	69.90	70.40	88.90	89.20	78.60	78.80
0.04	77.65	77.75	93.90	93.85	89.10	89.00
0.03	85.95	85.75	97.60	97.55	95.70	95.60
0.02	93.45	93.50	99.30	99.20	99.60	99.50
0.01	98.40	98.30	99.95	99.95	100	100

Note: Percentage of rejections at the 5% level when testing for $\mathcal{D} = 1$ according to (5).

As the shift probability increases, $\{\mu_t\}$ tends to behave like a random walk shifting every period. In this context, the rejection frequencies tend to be relatively moderate. For $p = 0.1$, these vary from around 32% to nearly 57%. On the other hand, with more infrequent shifts, the rejection frequencies largely increase. For $p = 0.01$, they are all above 98%. These figures can be compared with those provided by Diebold and Inoue (2001, Table 2) for the log-periodogram regression. In particular, given the sample lengths analyzed, their rejection rates vary between 26% and 38% for $p = 0.01$, and between 21.1% and 25.8% for $p = 0.1$, showing more conservative values. The differences in the results may stem ultimately from the differences in the rates of convergence of the estimators involved, which allows the DKH test to yield more efficient results in this context.

B) Markov switching mean function

Next, we consider the Markov switching mean function in (10). The main parameter of interest in this specification is δ, which controls the rate at which the transition probabilities from one state to another shrink to zero. We conduct the Monte Carlo experiment focusing on an increasing sequence of values for δ in the interval $[0, 1]$, namely, $\delta = 0, 0.2, ..., 1$, and set $\mu_0 = 0$ and $c_0 = c_1 = 0.9$, considering $\mu_1 \in \{0.1, 1\}$. Table 2 reports the sample frequency of rejections of the DKH tests given the different combinations of values.

Table 2: Markov switching mean from (10)

		T=250		T=500		T=1000	
μ_1	δ	t_ϕ^2	$\widetilde{t}_\phi^2$	t_ϕ^2	$\widetilde{t}_\phi^2$	t_ϕ^2	$\widetilde{t}_\phi^2$
0.1	0	5.10	5.60	6.85	7.45	12.95	12.95
	0.2	6.95	8.25	11.75	12.30	10.20	10.55
	0.4	19.80	21.15	37.70	38.00	50.15	50.75
	0.6	43.25	45.35	78.05	78.85	91.10	91.50
	0.8	71.00	72.45	97.65	97.65	99.85	99.90
	1.0	92.10	92.75	99.95	99.95	100	100
1	0	100	100	100	100	100	100
	0.2	89.55	90.55	99.85	99.90	100	100
	0.4	25.00	26.90	52.35	52.90	77.80	78.40
	0.6	17.55	18.50	41.00	42.05	76.85	76.90
	0.8	16.00	16.80	17.35	17.75	35.40	39.45
	1.0	42.40	42.45	51.85	52.15	52.40	52.20

Note: Percentage of rejections at the 5% level when testing for $\mathcal{D}= \delta/2$ according to (5).

In the case of small level shifts ($\mu_1 = 0.1$) the rejection rates grow with δ, which is intuitive: For $\delta = 0$ the probability to switch is 0.9, *i.e.* the mean changes almost every period but only by very little such that the changes are hardly recognizable. Consequently, $\{z_t\}$ from (4) essentially behaves like the white noise process $\{\varepsilon_t\}$ and the rejection rate for $\delta = 0$ is close to the nominal level. On the contrary, for larger jumps in level ($\mu_1 = 1$), processes with small values of δ lead particularly often to rejections.

C) Stopbreak model

Table 3 reports the results for the Stopbreak process from (13) with $\gamma_T(\delta) = T^\delta$ and δ taking the same values as in B) above. Note that for $\delta = 0$, the resulting process is again essentially a random walk plus noise and, consequently, the rejection frequencies are close to the nominal ones. On the other hand, for values $\delta > 0$, we observe considerable rejection rates that tend to grow with T.

Table 3: Stopbreak from (13)

	T=250		T=500		T=1000	
δ	t_ϕ^2	$\widetilde{t}_\phi^2$	t_ϕ^2	$\widetilde{t}_\phi^2$	t_ϕ^2	$\widetilde{t}_\phi^2$
0	4.55	5.15	4.20	4.45	4.80	4.85
0.2	20.90	22.85	41.95	42.20	60.25	60.70
0.4	53.05	53.80	73.40	73.80	91.40	91.25
0.6	56.45	57.35	62.95	63.50	74.25	74.45
0.8	45.45	46.00	45.75	45.90	49.65	50.10
1.0	35.05	35.95	36.85	36.95	37.55	38.00

Note: Percentage of rejections at the 5% level when testing for $\mathcal{D} = 1 - \delta$ according to (5).

D) Unobserved components model

Finally, Table 4 reports the frequencies of rejection for the local level from (17). We consider values $\lambda \in \{1, 10\}$ and the same sequence of values of δ used in B) and C) above. For $\delta = 1$, the process is a random walk plus noise, such that H_0 is rejected in roughly 5% of all cases. With a larger signal ($\lambda = 10$) the rejection frequencies are sizeable for $\delta < 1$ and growing with T, while with $\lambda = 1$ the rates are more moderate.

Table 4: Local level from (17)

		T=250		T=500		T=1000	
λ	δ	t_ϕ^2	$\widetilde{t}_\phi^2$	t_ϕ^2	$\widetilde{t}_\phi^2$	t_ϕ^2	$\widetilde{t}_\phi^2$
1	0	11.85	12.65	13.10	13.80	15.05	15.45
	0.2	10.65	11.95	13.45	14.50	18.85	19.30
	0.4	13.25	14.70	19.50	20.10	25.40	25.65
	0.6	14.70	15.85	19.95	20.35	30.05	30.20
	0.8	10.80	12.05	21.40	22.10	37.55	37.35
	1.0	4.10	4.55	4.55	5.00	4.55	5.00
10	0	52.55	51.65	85.85	83.60	91.65	89.85
	0.2	45.40	43.55	82.60	78.80	90.90	88.45
	0.4	34.20	32.15	71.15	65.65	83.05	78.25
	0.6	21.15	21.50	51.80	47.30	66.70	61.95
	0.8	9.50	10.45	23.60	23.45	34.80	33.70
	1.0	3.75	4.10	4.85	5.30	4.60	4.95

Note: Percentage of rejections at the 5% level when testing for $\mathcal{D} = \delta$ according to (5).

4 Testing against breaks in d

Several papers have addressed the detection of breaks in the order of fractional integration. Gil-Alana (2008), Sibbertsen and Kruse (2009), Hassler and Scheithauer (2011), Yamaguchi (2011) and Martins and Rodrigues (2012) allowed for just one unknown breakpoint, while Hassler and Meller (2014) treated the number of breaks as well as their timing as unknown. In this paper, we consider the situation where the sample is split exogenously into b non-overlapping subsamples or blocks,

$$t \in [T_{i-1} + 1, T_i] , \quad T_i = \lfloor \tau_i T \rfloor , \; i = 1, \ldots, b , \tag{22}$$

where $\tau_0 = 0$ and $\tau_b = 1$, such that each block contains $T_i - T_{i-1}$ observations. Let d_i denote the order of fractional integration over $[T_{i-1} + 1, T_i]$. Beran and Terrin (1996) treated the special case of $b = 2$ and test for equality of two parametric estimators, where they allowed the breakpoint to be unknown. Similarly to us, Kumar and Okimoto (2007) fixed the breakpoint exogenously, assuming $b = 2$, and compared the subsample estimates of a semi-parametric estimator. However, they had no asymptotic theory to rely on.

Shimotsu (2006) studied the specific situation where all blocks are of equal sample size T/b and constructed a Wald-type statistic when testing for the joint overall null hypothesis $d_1 = \cdots = d_b$. In our context, we would like to have a higher degree of flexibility. First, if the true breaks are not equi-spaced, then a correct timing is desirable to increase power. Second, we wish to compare the blocks separately and test, for example, whether the order of integration in the first and last one are equal. Consequently, the null hypotheses of our interest are:

$$\mathrm{H}_0^{(i,j)} : d_i = d_j \, , \quad i \neq j \, . \tag{23}$$

For given break fractions τ_i one may compute local Whittle estimators or Exact LW [ELW] estimators; see Robinson (1995) and Shimotsu and Phillips (2005), respectively, for definitions and asymptotic properties. Since ELW is valid also in the region of nonstationarity, we will employ this more refined estimator in our application. The estimators from each subsample are called $\widehat{d}_i$, $i = 1, \ldots, b$. They are semi-parametric and require the choice of a so-called bandwidth m_i for each block where

$$\frac{1}{m_i} + \frac{m_i}{T_i - T_{i-1}} \to 0 \tag{24}$$

as the sample size (in each block) increases. To test $\mathrm{H}_0^{(i,j)}$ we suggest to simply compute the appropriately normalized difference of two subsample estimators. The limiting distribution under the null hypothesis is given next.

Proposition. *Let $\widehat{d}_i$ and $\widehat{d}_j$, $i \neq j$, stand for the (Exact) Local Whittle estimators of the order of fractional integration d_0 computed from two non-overlapping subsamples where the bandwidths m_i and m_j satisfy* (24) *, $i, j = 1, \ldots, b$. Define the test statistic*

$$\mathcal{S}_{ij} = 2 \, \frac{\sqrt{m_i m_j}}{\sqrt{m_i + m_j}} \left(\widehat{d}_i - \widehat{d}_j \right) .$$

Under $H_0^{(i,j)}$ and (24) *and under the assumptions in Shimotsu (2006, Lemma 1 and 3) it follows that*

$$\mathcal{S}_{ij} \xrightarrow{D} \mathcal{N}(0,1), \tag{25}$$

where $\xrightarrow{D}$ denotes convergence in distribution.

Proof: It follows from the proofs of Lemma 1 and 3 in Shimotsu (2006) that $\sqrt{m_i}(\widehat{d}_i - d_0)$ and $\sqrt{m_j}(\widehat{d}_j - d_0)$ are asymptotically independent and obey asymptotically $\sqrt{m_i}(\widehat{d}_i - d_0) \xrightarrow{D} N(0, 1/4)$. Hence, the proof is straightforward to complete.

The limiting distribution of $\mathcal{S}_{ij}$ allows to test $\mathrm{H}_0^{(i,j)}$ against two- or one-sided alternatives.

5 Empirical results

The Great Recession of 2008 and the Euro area sovereign debt crisis, which started in early 2010, have originated great pressure on the banking sector. Over this period, banks faced an extremely uncertain operating environment, which has lead to repeated downgrades in ratings, the widening of funding spreads and the decline of equity prices, particularly in Europe and specifically in the European Monetary Union (EMU) and Southern Europe (Figure 2); see Chan-Lau, Liu and Schmittmann (2012).

[Insert Figures 1 and 2 about here]
[Insert Figures 3 and 4 about here]

In this section we characterize the persistence properties of the log of absolute bank equity index returns. The variable used in the analysis is constructed from the observable series of bank equity index returns r_t, *i.e.*, $z_t = \log(|\widehat{r}_t^*|)$, $t = 1, \ldots, T$, where $\widehat{r}_t^* = r_t - \widehat{\alpha}_0 - \widehat{\alpha}_1 r_{t-1} - \ldots - \widehat{\alpha}_p r_{t-p}$, with p selected based on the Schwarz information criteria (BIC)[4]. Our sample consists of daily data of market cap weighted indices and covers the period from January 01, 2003 to July 18, 2013. All data was obtained from Datastream.

We provide results for the complete sample (2752 observations), but we also split the sample into three parts: Subsample 1 corresponds to the period from January 01, 2003 to December 31, 2005 (783 observations); subsample 2 corresponds to the period from January 01, 2006 to December 31, 2008 (783 observations); and subsample 3 corresponds to the period from January 01, 2009 to July 18, 2013 (1186 observations). The choice of these three subsamples is motivated by the contrast that these allow us to establish. Subsample 1 corresponds to a period in which banks have operated without major global events affecting their activity; subsample 2 comprises the beginning of the current economic and financial crises and the collapse of the Lehman Brothers investment bank; and finally, subsample 3 includes the Euro area sovereign debt crisis, which started in early 2010 and has led to increased pressure in financial markets.

Considering subsamples 2 and 3 (as also suggested by Chan-Lau, Liu and Schmittmann, 2012), is of importance since while the 2008 Great Recession (subsample 2) affected the banking system worldwide, partly owing to the run on repurchase operations (Gorton and Metrick, 2012), in subsample 3 (the European sovereign debt crisis) a decoupling of the US economy (and other countries) from the Euro area has been observed, resulting in a globally heterogeneous recovery of the banking system.

From Figure 1 it is hard to make a case that there was a banking crisis unfolding before the start of the financial crises in the second half of 2007. We observe that although the

[4]We have also analysed the persistence of the log absolute return based on $\widehat{r}_t^*$ computed from an AR(1) model (as is frequently considered in the literature) and the results obtained are similar to the ones reported below.

crises had worldwide impact, the magnitude of its effects seems to have been more severe in North America (US in specific) and in Europe (particularly in the EMU and Southern Europe). Interestingly, Figure 1 (and corresponding to our subsample 3, *i.e.*, 2009 - 2013) also illustrates that Asia managed to return to equity price levels similar to those before the crisis and that in Latin America these grew even higher than before the crisis. Europe, on the other hand, seems to have stabilized at a lower level than before the crisis, but North America, which was severely affected in subsample 2, displays in this last period a growing trend. The contrast between the dynamics of the bank equity price index in Europe and the US, is a consequence of the weakening of the economic conditions in the Euro area and the contrasting positive signs of recovery in the US (as well as in major emerging countries); see for instance La Porta *et al.* (2002) and Cole, Moshirian and Wu (2008) for evidence on the relationship between bank stock returns and economic growth.

The extremely poor performance of the banking sector between 2006 and 2009 (subsample 2), is a consequence of the real-estate bubble in the US, the failure of the Lehman Brothers, and the deterioration of expectations about future economic activity that accompanied the collapse. As pointed out by Kho and Stulz (2000), banks' profits increase with the level of economic activity, so that banks' stocks suffer when economic growth lowers. The greater vulnerability of European banks may result from the fact that the banking system in this area is quite large. According to Shambaugh (2012), the total assets of the banking system in the European Union were equivalent to over 300 percent of euro-area GDP in 2007, whereas in the US these corresponded to less than 100 percent. Furthermore, the holding by many banks of marketable securities with increased exposure during the crisis, aggravated the situation, as the value of these marketable securities fell with the stock market. This was particularly dramatic in banks holding European government bonds, which had been regarded as risk-free assets before the crisis, but which during the crisis experienced large declines in value as a consequence of increased sovereign default risk (see Shambaugh, 2012, pp. 187-189). Note that in terms of European countries, Belgium, Greece, Ireland, Italy, Portugal and Spain observed the most severe increase in their CDS spreads over this period. However, even banks without substantial exposures to peripheral European government securities were affected, particularly those that were major counterparties in derivatives markets referencing these securities, and those who participated in large interest rate swaps with sovereigns, and/or had claims on banks highly exposed to peripheral sovereigns. These developments lead to pronounced equity price declines for European banks, which are far more exposed to European government securities, and more exposed to the risk of a potential default. Indeed, banks domiciled in peripheral European countries have performed the worst since 2007 (Chan-Lau, Liu and Schmittmann, 2012; Shambaugh, 2012). From Figure 3, we observe that from 2007 onwards particularly in Europe, EMU and Southern Europe there has been a marked increase in volatility.

Furthermore, as the crisis unfolded the situation aggravated particularly for European banks, which were confronted with US dollar funding shortages, and were forced to retreat from global operations such as trade finance in Asia and municipal finance in the US (Chan-Lau, Liu and Schmittmann, 2012). This led to a dramatic liquidity shortage, which originated an intervention by the European Central Bank (ECB), providing European banks with long-term (up to three years) financing in two allotments, one conducted in December 2011 and the other in February 2012 (Cour-Thimann and Winkler, 2013; and Shambaugh, 2012, pp.189-190). It is also important to note that banks' equity return performance was also being conditioned by stringent bank regulations and by the requirement of improved capital ratios, particularly by European Banks, to withstand potential sovereign debt losses. These regulations and capital requirements may have contributed to speed up the deleveraging process that started in 2008 and to further depress earnings in the banking sector (IMF, 2012).

To have a better understanding of the behaviour of bank equity index returns worldwide, in Table 5 we provide some descriptive statistics for several reference regions. We observe from this table that for the complete period under analysis the highest annual mean returns ($\overline{r}$) are obtained for Latin America ($\overline{r} = 18.10\%$) and the Emerging Markets ($\overline{r} = 14.55\%$), whereas the lowest were registered in Southern Europe ($\overline{r} = -5.00\%$) and the EMU ($\overline{r} = -4.19\%$). It can further be observed from the subsample analysis that all regions moved from a period of (high) positive returns (subsample 1), to a period in which all regions recorded negative returns (subsample 2). In the third period (subsample 3) a worldwide recovery is observed, with all regions, except for the EMU ($\overline{r} = -8.61\%$) and Southern Europe ($\overline{r} = -16.66\%$), registering positive annual average returns. Latin America ($\overline{r} = 13.79\%$) and Emerging Markets ($\overline{r} = 12.90\%$) are still the leading regions in terms of annual average return, with North America ($\overline{r} = 8.72\%$) and Asia ($\overline{r} = 8.16\%$) closely behind.

In terms of volatility we also observe from this table that when the complete sample is considered the EMU ($\widehat{\sigma} = 34.06$), North America ($\widehat{\sigma} = 33.74$), Southern Europe ($\widehat{\sigma} = 33.41$) and Europe ($\widehat{\sigma} = 30.54$) display the highest volatility, and that Asia observes the lowest ($\widehat{\sigma} = 21.48$). Contrasting the results for the three subsamples considered, we observe a global increase in volatility in the 2006 - 2009 period, with North America presenting a sizeable higher value than any other region ($\widehat{\sigma} = 41.34$). However, between 2009 and 2013 there is a worldwide decrease in volatility except in Europe where a marked increase is observed (particularly in the EMU ($\widehat{\sigma} = 42.68$) and Southern Europe ($\widehat{\sigma} = 42.92$)).

Table 5: Descriptive statistics for bank equity index returns for several reference regions (2003 - 2013)

	2003 - 2013				2003 - 2006				2006 - 2009				2009 - 2013			
Region/Area	$\overline{r}$	σ	skew	κ	$\overline{r}$	σ	skew	κ	$\overline{r}$	σ	skew	κ	$\overline{r}$	σ	skew	κ
ASIA	7.45	21.48	-0.23	9.58	26.20	16.14	-0.40	7.76	-12.37	27.67	-0.17	9.18	8.16	19.81	-0.07	5.42
EMU	-4.19	34.06	0.13	9.23	23.21	14.85	-0.04	4.59	-24.90	33.11	-0.05	12.04	-8.61	42.68	0.22	5.78
EU	-2.06	31.83	0.10	10.61	19.69	14.07	0.05	4.54	-27.10	33.36	0.09	13.43	0.11	38.52	0.13	6.44
EUROPE	-0.38	30.54	0.06	10.84	21.07	14.01	0.01	4.58	-26.28	33.31	0.14	13.72	2.56	36.06	0.07	6.29
SOUTH. EUROPE	-5.00	33.41	0.18	9.63	23.33	14.17	-0.16	3.94	-15.68	30.50	0.04	13.98	-16.66	42.92	0.25	5.84
FAR EAST	5.63	23.51	-0.14	9.88	27.11	18.00	-0.27	7.42	-14.20	30.05	-0.08	9.87	4.55	21.71	-0.03	5.31
EMERG. MARKETS	14.55	21.79	-0.39	10.91	35.68	13.23	-0.50	5.45	-4.08	29.17	-0.30	9.49	12.90	20.57	-0.24	5.85
G7	-0.40	25.13	-0.03	13.62	17.09	11.33	0.04	4.94	-26.16	28.71	-0.02	13.28	5.06	28.89	0.02	9.46
LATIN AMERICA	18.10	26.44	-0.40	10.12	40.92	17.83	-0.26	4.05	1.80	34.82	-0.35	9.44	13.79	24.71	-0.30	5.42
NORTH AMERICA	0.24	33.74	0.07	18.71	12.12	12.89	0.04	4.19	-24.49	41.34	-0.12	14.12	8.72	37.46	0.28	14.71
WORLD	3.08	21.55	-0.12	12.42	19.54	10.43	-0.16	4.73	-20.26	25.97	-0.03	12.73	7.62	23.65	-0.08	7.55

Note: $\overline{r}$ and σ refer to the annualised mean and standard deviation of returns, respectively, and skew and κ to skewness and kurtosis.

5.1 Order of fractional integration

Tables 6 - 8 present the estimates of d computed using the Exact Local Whittle (ELW) estimator ($\widehat{d}_{ELW}$) as well as their 95% confidence intervals (which we denote by $CI^{95\%}_{ELW}$) for the 11 reference regions and sectors, and 36 countries, respectively, under analysis. The bandwidth used in the ELW estimator is $m = T^{0.65}$ for the full sample and similarly $m_i = (T_i - T_{i-1})^{0.65}$ for the subsamples. We also compute LM tests based confidence intervals, which we denote by $CI^{95\%}_{LM}$. These confidence intervals are computed via a grid search, based on which we determine the range of values d_0 not rejected by the fractional integration test at the 5% significance level. Following Hassler, Rodrigues, and Rubia (2009, Remark 2.7) we thus obtain numerically 95% confidence intervals[5]. In situations of Section 3 where the rejection probabilities are close to one, such confidence intervals would be empty for processes with spurious long memory. For all series considered, however, the confidence intervals constructed from non-rejection are non-empty, so that we have some confidence that the data is generated by true fractional integration.

From Table 6 we observe that, for the 11 regional and sectorial log of absolute bank equity index returns considered, the minimum and maximum estimates of d_i, $i = 1, ..., 11$, obtained were: i) for the complete sample, $0.30 \leq \widehat{d}^{Full}_{ELW} \leq 0.42$; ii) for subsample 1, $0.15 \leq \widehat{d}^{Sub1}_{ELW} \leq 0.27$; iii) for subsample 2, $0.32 \leq \widehat{d}^{Sub2}_{ELW} \leq 0.44$; and iv) for subsample 3, $0.14 \leq \widehat{d}^{Sub3}_{ELW} \leq 0.39$. These results seem to suggest that although overall all log of absolute bank equity index returns are stationary there is heterogeneity across indices and across subsamples, which is corroborated by the computed confidence intervals (Table 6). From the analysis of the confidence intervals we observe that $CI^{95\%}_{LM}$ are shifted to the right, comparatively to $CI^{95\%}_{ELW}$, but both provide qualitatively the same conclusions with regards the dynamics of the persistence over the three subsamples considered. In general, we observe a shift of both intervals from subsample 1 to subsample 2, suggesting an increase in persistence, and a shift again from subsample 2 to subsample 3, suggesting a reduction in persistence.

Regarding the 36 country specific log of absolute bank equity index returns, we observe from Tables 7 and 8 that the degree of heterogeneity seems to be larger then in the regional case, in particular i) for the complete sample, $0.12 \leq \widehat{d}^{Full}_{ELW} \leq 0.45$; ii) for subsample 1, $0.00 \leq \widehat{d}^{Sub1}_{ELW} \leq 0.39$; iii) for subsample 2, $0.17 \leq \widehat{d}^{Sub2}_{ELW} \leq 0.48$; and iv) for subsample 3, $0.08 \leq \widehat{d}^{Sub3}_{ELW} \leq 0.44$.

Interestingly, when the full sample is considered the only country specific log of absolute bank equity index returns with a $\widehat{d}^{Full}_{ELW} \leq 0.2$ (*i.e.* with the lowest order of integration) correspond to Argentina. However, if subsample 1 is considered we observe that 19 out of the 36 indices have an estimated $\widehat{d}^{Sub1}_{ELW} \leq 0.2$ and only Spain, Germany, Belgium and the Netherlands present a $\widehat{d}^{Sub1}_{ELW} \geq 0.3$. In subsample 2 (period of the Lehman Brothers collapse)

[5] For Emergin Markets (Subsample 1), Argentina (Subsamples 2 and 3), Hungary (Subsample 1), Korea (Subsample 1), Norway (Subsample 1) and Spain (Subsample 3), in order to obtain left bounded intervals, extreme observations had to be accounted for. In particular, observations such that $z_t \leq -4$ were filtered out. Note that these corresponded to a small number of observations.

the number of log of absolute bank equity index returns series with $\widehat{d}_{ELW}^{Sub2} \leq 0.2$ reduces from 19 to 3. The smallest orders of integration are observed for Hungary, Thailand and Indonesia. However, in contrast the number of countries with log of absolute bank equity index returns with a $\widehat{d}_{ELW}^{Sub2} \geq 0.3$ increases considerably. In particular, in comparison to subsample 1, the number of countries with a $\widehat{d}_{ELW}^{Sub2} \geq 0.3$ increases from 4 to 22, but in general an overall increase in the values of the estimated order of integration is observed in this subsample for all countries, highlighting the global impact that the financial crises and the Lehman Brothers collapse had on Banks worldwide. Interestingly, the countries with the largest order of integration in this period are the US, Belgium and Slovenia, all with a $\widehat{d}_{ELW}^{Sub2} \geq 0.45$. Finally, in subsample 3 (period of the European Sovereign debt) the number of log of absolute bank equity index returns series with a $\widehat{d}_{ELW}^{Sub3} \leq 0.2$ increases (in comparison to subsample 2) to 14, of which the countries with lowest orders of integration are the Netherlands ($\widehat{d}_{ELW}^{Sub3} = 0.13$), Argentina ($\widehat{d}_{ELW}^{Sub3} = 0.11$), and Japan ($\widehat{d}_{ELW}^{Sub3} = 0.08$). However, in this group (with $\widehat{d}_{ELW}^{Sub3} \leq 0.2$) are also European countries, such as Denmark, Greece, the Netherlands, Portugal, Spain and Italy. Furthermore, the number of log of absolute bank equity index returns series with $\widehat{d}_{ELW}^{Sub3} \geq 0.3$ in this period reduces to 8 (recall that in Subsample 2, $\widehat{d}_{ELW}^{Sub3} \geq 0.3$ was observed for 22 countries).

Table 6: Long-memory behaviour of regional bank sector log absolute returns

	2003-2013			2003-2006			2006-2009			2009-2013		
	$\widehat{d}_{ELW}^{Full}$	$CI_{ELW}^{95\%}$	$CI_{LM}^{95\%}$	$\widehat{d}_{ELW}^{Sub1}$	$CI_{ELW}^{95\%}$	$CI_{LM}^{95\%}$	$\widehat{d}_{ELW}^{Sub2}$	$CI_{ELW}^{95\%}$	$CI_{LM}^{95\%}$	$\widehat{d}_{ELW}^{Sub3}$	$CI_{ELW}^{95\%}$	$CI_{LM}^{95\%}$
ASIA	0.34	[0.26;0.41]	[0.34;0.49]	0.18	[0.07;0.29]	[-0.09;0.26]	0.34	[0.23;0.45]	[0.31;0.53]	0.33	[0.23;0.43]	[0.29;0.49]
EMERG. MARK.	0.35	[0.27;0.42]	[0.33;0.50]	0.23	[0.12;0.34]	[-0.09;0.39]	0.37	[0.25;0.48]	[0.27;0.53]	0.31	[0.22;0.41]	[0.30;0.51]
EMU	0.35	[0.28;0.43]	[0.38;0.52]	0.25	[0.14;0.36]	[0.17;0.44]	0.33	[0.22;0.45]	[0.26;0.53]	0.21	[0.11;0.31]	[0.15;0.41]
EU	0.37	[0.29;0.44]	[0.38;0.52]	0.24	[0.13;0.35]	[0.17;0.41]	0.35	[0.23;0.46]	[0.27;0.52]	0.24	[0.14;0.33]	[0.17;0.43]
EUROPE	0.34	[0.26;0.41]	[0.37;0.50]	0.23	[0.12;0.34]	[0.18;0.41]	0.37	[0.26;0.49]	[0.29;0.53]	0.26	[0.16;0.36]	[0.20;0.42]
SOUTH. EUR.	0.35	[0.27;0.42]	[0.37;0.50]	0.15	[0.03;0.26]	[0.13;0.39]	0.38	[0.27;0.49]	[0.32;0.53]	0.14	[0.04;0.24]	[0.01;0.32]
FAR EAST	0.31	[0.24;0.39]	[0.32;0.47]	0.17	[0.05;0.28]	[-0.08;0.27]	0.35	[0.24;0.46]	[0.30;0.51]	0.32	[0.22;0.42]	[0.27;0.51]
G7	0.39	[0.32;0.47]	[0.41;0.55]	0.15	[0.03;0.26]	[0.15;0.37]	0.37	[0.26;0.48]	[0.34;0.54]	0.30	[0.21;0.40]	[0.31;0.51]
LATIN AMER.	0.30	[0.23;0.38]	[0.20;0.42]	0.20	[0.08;0.31]	[0.02;0.35]	0.32	[0.21;0.43]	[0.07;0.58]	0.27	[0.17;0.37]	[0.12;0.46]
N.AMERICA	0.42	[0.35;0.50]	[0.44;0.57]	0.24	[0.13;0.36]	[0.18;0.49]	0.44	[0.32;0.55]	[0.41;0.59]	0.39	[0.29;0.49]	[0.38;0.59]
WORLD	0.35	[0.28;0.43]	[0.37;0.51]	0.27	[0.16;0.38]	[0.11;0.40]	0.33	[0.32;0.54]	[0.35;0.61]	0.31	[0.21;0.40]	[0.29;0.47]

Note: $CI_{ELW}^{95\%}$ and $CI_{LM}^{95\%}$ represent 95% confidence intervals computed based on the Exact Local Whittle (ELW) estimator with bandwidth $m = T^{0.65}$, and based on the Lagrange Multiplier (LM) test procedure, respectively.

Table 7: Long-memory behaviour of country bank sector log absolute returns

	2003-2013			2003-2006			2006-2009			2009-2013		
	$\widehat{d}_{ELW}^{Full}$	$\mathrm{CI}_{ELW}^{95\%}$	$\mathrm{CI}_{LM}^{95\%}$	$\widehat{d}_{ELW}^{Sub1}$	$\mathrm{CI}_{ELW}^{95\%}$	$\mathrm{CI}_{LM}^{95\%}$	$\widehat{d}_{ELW}^{Sub2}$	$\mathrm{CI}_{ELW}^{95\%}$	$\mathrm{CI}_{LM}^{95\%}$	$\widehat{d}_{ELW}^{Sub3}$	$\mathrm{CI}_{ELW}^{95\%}$	$\mathrm{CI}_{LM}^{95\%}$
ARGENTINA	0.12	[0.05;0.20]	[-0.05;0.21]	0.14	[0.03;0.25]	[-0.04;0.25]	0.23	[0.11;0.34]	[-0.17;0.36]	0.11	[0.02;0.19]	[-0.38;0.20]
AUSTRALIA	0.32	[0.24;0.39]	[0.33;0.49]	0.12	[0.01;0.24]	[-0.09;0.36]	0.37	[0.25;0.48]	[0.29;0.55]	0.30	[0.21;0.40]	[0.17;0.46]
AUSTRIA	0.28	[0.20;0.35]	[0.23;0.38]	0.06	[-0.06;0.17]	[-0.13;0.16]	0.29	[0.18;0.41]	[0.24;0.52]	0.28	[0.18;0.38]	[0.17;0.50]
BELGIUM	0.40	[0.32;0.47]	[0.38;0.53]	0.33	[0.21;0.44]	[0.25;052]	0.45	[0.33;0.56]	[0.33;0.62]	0.25	[0.15;0.35]	[0.23;0.49]
CANADA	0.36	[0.28;0.43]	[0.34;0.48]	0.13	[0.02;0.25]	[-0.10;0.32]	0.40	[0.29;0.52]	[0.28;0.52]	0.37	[0.27;0.46]	[0.29;0.51]
CHILE	0.26	[0.18;0.33]	[0.18;0.42]	0.14	[0.02;0.25]	[-0.02;0.32]	0.28	[0.17;0.40]	[-0.03;0.41]	0.16	[0.06;0.26]	[0.08;0.35]
COLOMBIA	0.26	[0.18;0.33]	[0.17;0.39]	0.29	[0.18;0.40]	[0.19;0.48]	0.27	[0.16;0.39]	[0.07;0.47]	0.15	[0.05;0.25]	[0.00;0.27]
DENMARK	0.28	[0.20;0.35]	[0.27;0.41]	0.14	[0.03;0.26]	[0.11;0.35]	0.37	[0.25;0.48]	[0.25;0.54]	0.19	[0.09;0.28]	[0.06;0.33]
FINLAND	0.32	[0.25;0.40]	[0.32;0.47]	0.24	[0.12;0.35]	[0.15;0.45]	0.27	[0.15;0.38]	[0.17;0.44]	0.28	[0.18;0.38]	[0.28;0.51]
FRANCE	0.31	[0.23;0.38]	[0.29;0.46]	0.24	[0.13;0.35]	[0.21;0.44]	0.38	[0.26;0.49]	[0.22;0.54]	0.30	[0.20;0.39]	[0.10;0.41]
GERMANY	0.37	[0.30;0.45]	[0.32;0.50]	0.36	[0.25;0.48]	[0.32;0.57]	0.35	[0.24;0.46]	[0.30;0.56]	0.24	[0.14;0.34]	[0.13;0.44]
GREECE	0.36	[0.29;0.43]	[0.34;0.47]	0.09	[-0.02;0.20]	[-0.17;0.25]	0.31	[0.19;0.42]	[0.18;0.46]	0.19	[0.09;0.28]	[0.00;0.28]
HONG KONG	0.30	[0.22;0.37]	[0.25;0.43]	0.17	[0.06;0.29]	[0.14;0.37]	0.32	[0.21;0.43]	[0.31;0.54]	0.29	[0.19;0.38]	[0.19;0.43]
HUNGARY	0.25	[0.18;0.33]	[0.23;0.40]	0.10	[-0.02;0.21]	[-0.34;0.13]	0.20	[0.18;0.41]	[0.15;0.45]	0.22	[0.12;0.32]	[0.18;0.44]
INDIA	0.24	[0.16;0.31]	[0.20;0.37]	0.15	[0.03;0.26]	[0.02;0.27]	0.30	[0.19;0.41]	[0.22;0.50]	0.22	[0.12;0.32]	[0.09;0.36]
INDONESIA	0.21	[0.13;0.28]	[0.12;0.28]	0.22	[0.11;0.34]	[0.16;0.39]	0.17	[0.06;0.28]	[-0.21;0.21]	0.18	[0.09;0.28]	[0.07;0.35]
IRELAND	0.39	[0.31;0.46]	[0.40;0.52]	0.10	[-0.01;0.21]	[-0.01;0.28]	0.41	[0.30;0.52]	[0.41;0.64]	0.25	[0.15;0.35]	[0.22;0.43]
ISRAEL	0.25	[0.18;0.32]	[0.28;0.43]	0.20	[0.08;0.31]	[0.08;0.34]	0.28	[0.17;0.40]	[0.09;0.47]	0.16	[0.07;0.26]	[0.14;0.34]
ITALY	0.33	[0.26;0.41]	[0.33;0.46]	0.28	[0.17;0.40]	[0.24;0.44]	0.36	[0.25;0.47]	[0.29;0.60]	0.20	[0.10;0.30]	[0.10;0.39]
JAPAN	0.25	[0.17;0.32]	[0.16;0.35]	0.21	[0.10;0.33]	[0.14;0.39]	0.36	[0.24;0.47]	[0.24;0.49]	0.08	[-0.01;0.18]	[-0.09;0.18]
KOREA	0.22	[0.14;0.29]	[0.17;0.37]	0.15	[0.04;0.26]	[-0.16;0.26]	0.31	[0.20;0.42]	[0.26;0.50]	0.24	[0.14;0.33]	[0.21;0.41]

Please see note under Table 6.

Table 8: Long-memory behaviour of country bank sector log absolute returns

	2003-2013			2003-2006			2006-2009			2009-2013		
	$\widehat{d}^{Full}_{ELW}$	$\mathrm{CI}^{95\%}_{ELW}$	$\mathrm{CI}^{95\%}_{LM}$	$\widehat{d}^{Sub1}_{ELW}$	$\mathrm{CI}^{95\%}_{ELW}$	$\mathrm{CI}^{95\%}_{LM}$	$\widehat{d}^{Sub2}_{ELW}$	$\mathrm{CI}^{95\%}_{ELW}$	$\mathrm{CI}^{95\%}_{LM}$	$\widehat{d}^{Sub3}_{ELW}$	$\mathrm{CI}^{95\%}_{ELW}$	$\mathrm{CI}^{95\%}_{LM}$
LUXEMBURG	0.40	[0.33;0.48]	[0.33;0.52]	0.29	[0.18;0.41]	[0.20;0.55]	0.43	[0.31;0.54]	[0.42;0.65]	0.44	[0.35;0.54]	[0.12;0.62]
MEXICO	0.29	[0.22;0.37]	[0.25;0.44]	0.26	[0.15;0.37]	[0.13;0.44]	0.25	[0.14;0.37]	[0.15;0.48]	0.20	[0.10;0.30]	[0.08;0.35]
NETHERLAND	0.31	[0.24;0.39]	[0.31;0.48]	0.31	[0.20;0.43]	[0.01;0.34]	0.38	[0.27;0.49]	[0.31;0.58]	0.13	[0.03;0.23]	[-0.01;0.26]
NORWAY	0.31	[0.24;0.39]	[0.30;0.45]	0.00	[-0.11;0.12]	[-0.35;0.13]	0.35	[0.24;0.46]	[0.28;0.53]	0.28	[0.18;0.37]	[0.26;0.46]
POLAND	0.24	[0.17;0.32]	[0.20;0.38]	0.08	[-0.04;0.19]	[-0.06;0.19]	0.21	[0.10;0.33]	[-0.06;0.36]	0.36	[0.26;0.46]	[0.21;0.51]
PORTUGAL	0.33	[0.26;0.41]	[0.36;0.47]	0.08	[-0.03;0.19]	[-0.09;0.22]	0.36	[0.25;0.48]	[0.27;0.55]	0.18	[0.09;0.28]	[0.10;0.34]
SINGAPORE	0.30	[0.23;0.38]	[0.26;0.42]	0.25	[0.13;0.36]	[0.13;0.37]	0.29	[0.18;0.40]	[0.19;0.47]	0.26	[0.17;0.36]	[0.24;0.43]
SLOVENIA	0.37	[0.29;0.44]	[0.38;0.51]	0.10	[-0.01;0.21]	[0.01;0.31]	0.45	[0.33;0.56]	[0.32;0.60]	0.31	[0.21;0.41]	[0.26;0.45]
SPAIN	0.35	[0.27;0.42]	[0.29;0.46]	0.39	[0.28;0.50]	[0.33;0.60]	0.39	[0.28;0.50]	[0.17;0.51]	0.20	[0.10;0.30]	[-0.13;0.39]
SWEDEN	0.32	[0.25;0.40]	[0.30;0.46]	0.25	[0.14;0.37]	[0.11;0.39]	0.29	[0.17;0.40]	[0.11;0.42]	0.32	[0.22;0.42]	[0.25;0.52]
SWITZ	0.32	[0.24;0.39]	[0.31;0.47]	0.23	[0.11;0.34]	[0.21;0.46]	0.31	[0.20;0.42]	[0.24;0.54]	0.24	[0.14;0.34]	[0.20;0.43]
TAIWAN	0.21	[0.14;0.29]	[0.17;0.35]	0.18	[0.07;0.29]	[-0.08;0.30]	0.24	[0.13;0.35]	[0.10;0.42]	0.21	[0.11;0.31]	[0.13;0.37]
THAILAND	0.23	[0.16;0.30]	[0.20;0.40]	0.16	[0.05;0.27]	[0.13;0.35]	0.20	[0.09;0.32]	[0.08;0.39]	0.19	[0.09;0.29]	[0.06;0.38]
UK	0.35	[0.27;0.42]	[0.30;0.45]	0.29	[0.17;0.40]	[0.17;0.46]	0.43	[0.32;0.54]	[0.35;0.66]	0.28	[0.18;0.38]	[0.25;0.48]
US	0.45	[0.37;0.52]	[0.46;0.58]	0.27	[0.16;0.38]	[0.20;0.51]	0.48	[0.37;0.60]	[0.47;0.65]	0.34	[0.24;0.44]	[0.33;0.52]

Please see note under Table 6.

5.2 Testing for breaks in persistence

In this section we investigate whether persistence has changed between the three periods under analysis. Hence, based on the three subsamples considered we expect that the order of integration increases from subsample 1 to subsample 2 (*i.e.*, $d_1 < d_2$) and that it decreases from subsample 2 to subample 3 (*i.e.* $d_3 < d_2$) and we therefore exploit this information using one-sided tests for breaks. However, we do not have any *a priori* expectations as to the direction of change from subsample 1 to subsample 3, and therefore apply two-sided tests in this case. Tables 9 and 10 report the test results at the Region/Area level, and at the country level, respectively.

Table 9: Tests for breaks in d between periods - Regions and Areas

	$\mathcal{S}_{13}$	$\mathcal{S}_{21}$	$\mathcal{S}_{32}$
ASIA	-1.934*	2.112**	-0.312
EMERG. MARKETS	-2.262**	2.855***	-0.775
EMU	0.942	0.810	-1.803**
EU	-0.492	1.537*	-1.143
EUROPE	-0.284	1.224	-1.019
SOUTH. EUROPE	-0.435	2.228**	-1.935**
FAR EAST	-2.058**	2.136**	-0.214
G7	-1.575	2.637***	-1.230
LATIN AMERICA	-1.185	1.578*	-0.494
N.AMERICA	-1.732*	2.312**	-0.727
WORLD	-0.702	1.361*	-0.746

Note: *, **, *** refer to 10%, 5% and 1% significance levels.

From our conjecture made at the beginning of this section, we expect $\mathcal{S}_{21} \geq 0$ if in fact an increase in d from subsample 1 to subsample 2 is observed and $\mathcal{S}_{32} \leq 0$ if a decrease in d occurs from subsample 2 to subsample 3. The results in Tables 9 and 10 are generally supportive of this conjecture. Furthermore, from Table 9 we observe that only for Europe and EMU did the persistence not change from the first subsample (2003 - 2006) to the second subsample (2006 - 2009), for all other regions (areas) considered a statistically significant increase was observed. For the country-specific indices qualitatively similar conclusions can be drawn, *i.e.*, in general the results validate our conjecture ($\mathcal{S}_{21} \geq 0$) and out of the 36 countries considered around 61% register a statistical significant increase in d from subsample 1 to subsample 2. The European countries that do not observe a change are Finland, Germany, Italy, the Netherlands and Spain.

In subperiod 3, as previously indicated, European banks were confronted with funding shortages, more stringent bank regulations, and the need to improve capital ratios. Furthermore, over this period the ECB had a major intervention, providing European banks with long-term financing. Hence, we expect in this period, particularly for European Banks, that a further change in persistence is observed. In particular, the intervention of the ECB must have had an impact on the duration of shocks, contributing to a reduction of persistence in the EMU countries, *i.e.*, we expect that $\mathcal{S}_{32} \leq 0$. This is clearly confirmed in Table 9, as a statistically significant reduction is observed for the EMU and Southern Europe.

At the country level (Table 10), the hypothesis that $d_2 \geq d_3$ is also validated. Notice that of the countries that constitute the EMU, Austria, Finland, and Luxemburg did not reject the null hypothesis of the same order of integration in subsamples 2 and 3.

Table 10: Tests for breaks in d between periods - Countries

Country	$\mathcal{S}_{13}$	$\mathcal{S}_{21}$	$\mathcal{S}_{32}$	Country	$\mathcal{S}_{13}$	$\mathcal{S}_{21}$	$\mathcal{S}_{32}$
ARGENTINA	1.189	1.444*	-2.725***	ITALY	0.559	0.871	-1.485*
AUSTRALIA	-2.523**	2.569***	-0.209	JAPAN	1.971**	1.180	-3.226***
AUSTRIA	-2.467**	2.293**	0.027	KOREA	-0.629	1.653**	-1.129
BELGIUM	1.487	1.451*	-3.031***	LUXEMBURG	-0.981	2.016**	-1.163
CANADA	-3.676***	3.011***	0.474	MEXICO	0.582	0.083	-0.671
CHILE	-0.415	0.675	-0.303	NETHERLANDS	2.657***	0.251	-2.924***
COLOMBIA	1.432	-0.178	-1.243	NORWAY	-3.520***	4.191***	-0.938
DENMARK	-0.447	2.841***	-2.575***	POLAND	-3.189***	2.127**	0.927
FINLAND	-0.652	0.592	0.022	PORTUGAL	-0.824	3.681***	-3.092***
FRANCE	-0.591	1.977**	-1.513*	SINGAPORE	-0.562	0.702	-0.184
GERMANY	2.141**	-0.032	-2.106**	SLOVENIA	-2.676***	4.177***	-1.767**
GREECE	-0.438	1.644*	-1.311*	SPAIN	2.055**	-0.434	-1.594*
HONG KONG	-2.200**	2.464***	-0.421	SWEDEN	-1.633	1.785**	-0.265
HUNGARY	-1.250	2.035**	-0.915	SWITZ	-0.017	1.331*	-1.399*
INDIA	-1.496	1.715**	-0.329	TAIWAN	-0.219	0.132	0.078
INDONESIA	0.368	-0.765	0.446	THAILAND	-0.550	0.785	-0.285
IRELAND	-1.477	3.708***	-2.467***	UK	0.357	1.645**	-2.107**
ISRAEL	0.639	0.416	-1.082	US	-1.420	3.277***	-2.066**

Note: *, **, *** refer significance at the 10%, 5% and 1% significance levels.

6 Concluding remarks

Diebold and Inoue (2001) and Granger and Hyung (2004), among others, showed that certain processes displaying "spurious long memory" are mistaken as fractionally integrated when testing by means of the log-periodogram regression for $d = 0$ or $d = 1$. Those processes are summable of a certain order $\mathcal{D}$ in the sense of Berenguer-Rico and Gonzalo (2014), and the variance of their sample means behaves like that of a fractionally integrated process of order $\mathcal{D}$. In a Monte Carlo exercise we show, however, that the fractional integration test by

Demetrescu *et al.* (2008) may discriminate between summability of order $\mathcal{D}$ and integration of order $\mathcal{D}$, where the power depends on the specific parameter constellation. For applied work we suggest the numerical determination of the interval of values of $\mathcal{D}$ where the test does not reject at a significance level α. If the interval turns out to be empty, then one may conclude that the process is not fractionally integrated but rather displays spurious long memory. Otherwise, this range of non-rejected values may serve as a $100\,(1-\alpha)\%$ confidence interval for the order of fractional integration; see Hassler, Rodrigues and Rubia (2009, Remark 2.7).

If one has confidence in the fractionally integrated (or "true long memory") model then the question naturally arises whether the memory is constant over time or subject to change. To test this null hypothesis we suggest splitting the sample of interest into non-overlapping subsamples where the break dates are given exogenously according to major political or economic upheavals. For each subperiod the order of integration is estimated using the exact local Whittle estimator. For any two subperiods of interest one then may test against the alternative that the respective memory parameters differ. The test statistic is the normalized difference of the estimators and follows a limiting standard normal distribution under the null hypothesis of no change.

The two procedures just summarized are applied to the log of absolute bank equity index returns of several regions of the world and several countries. Overall, the results obtained allow us to conclude that the series analysed in this paper display true long-memory features. A further interesting result obtained, using the breaks test introduced in Section 4, is that the order of fractional integration of the series analysed displays heterogeneous behaviour across the regions and countries considered, and over the periods analysed. This is particularly noticeable when considering subsamples 2 and 3, from which it can be seen that the Lehman Brothers collapse had a global impact originating increases in persistence worldwide, whereas in subsample 3 the sovereign debt in Europe and the different economic growth dynamics observed, among others, originated a significant decrease in persistence in some regions and countries.

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Figure 1: Log of the bank equity price index for several reference regions and areas

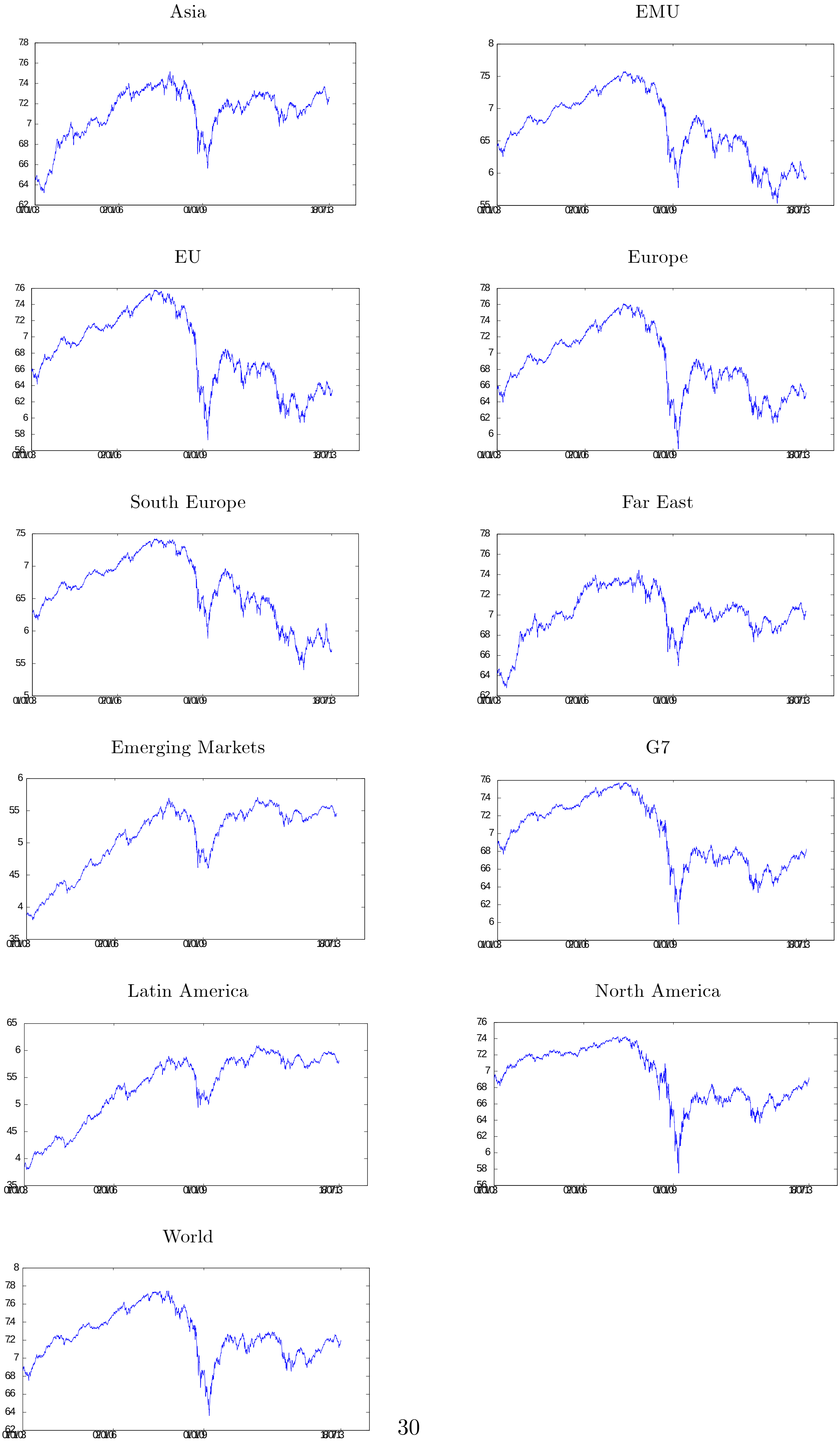

Figure 2: Bank equity returns for several reference regions and areas

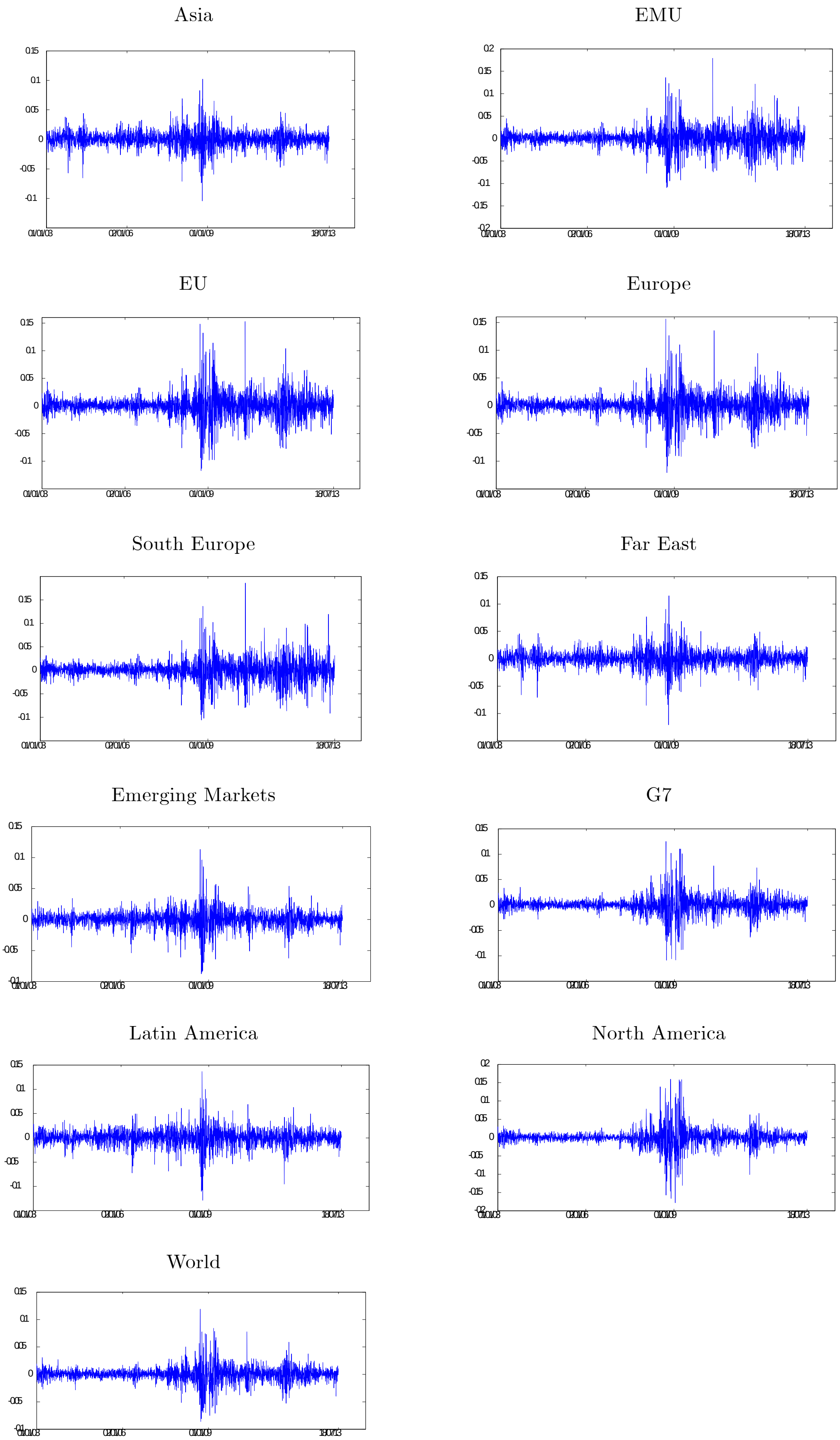

Figure 3: Absolute bank equity returns for several reference regions and areas

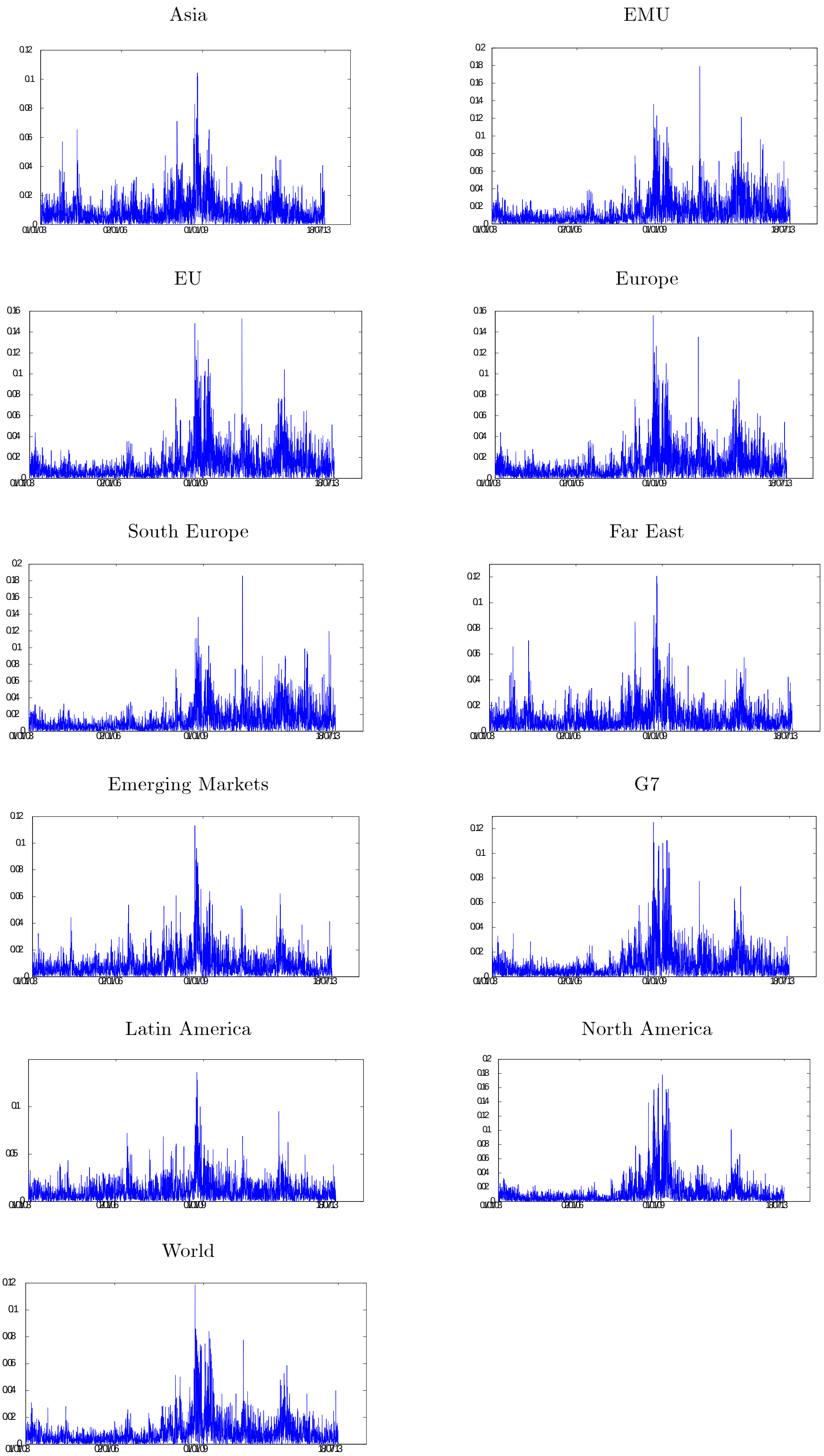

Figure 4: Log of absolute bank equity returns for several reference regions and areas