The 2007-? financial crisis: a money market perspective

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Abstract

The evolution of the spreads between unsecured money market rates of various maturities and central banks’ key policy rates has been subject to considerable debate and controversy in relation to the worldwide financial market turbulence that started in August 2007. Our contribution to the ongoing debate on the dynamics of money market spreads is empirical and methodological, motivated by the "shocking" evidence of non-stationary behaviour of money market spreads. In fact, in our view, empirical work testing the effectiveness of central bank policies has largely overlooked the complexity of the market environment and its implications for the statistical properties of the data. Thus, our main goal is to carefully document the "fingerprint" of money market turbulence, in the framework of a new econometric framework, allowing to incorporate policy interventions as well, and therefore well suited for testing their impact, whilst carefully accounting for the persistence properties of the data.

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1 Introduction

The evolution of the spreads between unsecured money market rates of various maturities and central banks’ key policy rates has been subject to considerable debate and controversy in relation to the worldwide financial market turbulence that started in August 2007. There are two dimensions in the debate, one macroeconomic and the other microstructural. The macroeconomic perspective is related to the short-cut approach followed in most macroeconomic models which is to assume that the central bank controls (by whatever means) the interest rate that is relevant, directly, for the investment and consumption decisions of economic agents; or, in more sophisticated macroeconomic models, the central bank may be able to steer, via arbitrage arguments, a (single) term structure of interest rates pricing the expected path of future policy rates plus a term premium (time-varying or not). With a term structure of interest rates in the macroeconomic model both short- and long-term interest rates may affect the investment and saving decisions of economic agents and thereby influence macroeconomic outcomes. However, the recent turbulence in money, credit and financial markets raised some questions about the "controlability" by central banks of the term structure of interest rates. In fact, whilst central banks have generally kept close control of very-short term unsecured money market rates (i.e. for overnight interbank deposits) and were also able to keep a steady influence on some longer-term money market interest rates (e.g. overnight index swap rates and general collateral repo rates), central banks seemed at pains to steer the evolution of the term structure of unsecured money market rates (i.e. LIBOR rates) at least in the early stages of the crisis. Still, as the latter rates are those used by investors and other market participants as indexing for derivatives contracts, and by banks to set interest rates on mortgage rates for households and rates on short-term financing for firms’ working capital and other longer-term financing, it is those rates that may be of relevance to gauge the monetary policy stance and its appropriateness. Thus, macroeconomic models should be able to incorporate those factors that make it more difficult for the central banks to influence the financing costs of the whole economy thereby hampering the transmission mechanism of monetary policy.

This leads one to the other side of the controversy which is about which are the microstructural factors that may explain the (existence and) divergence and instability in the evolution of the interest rates of various money market instruments (i.e. their spreads). If those spreads are constant, or predictable with a great degree of confidence, the short-cut of a single and "controlable" short-end of the term structure of interest rates may be an acceptable simplification for macroeconomic modelling. Indeed, until August
2007 this was the prevailing view that was grounded on solid empirical evidence for the main currency areas over the last decades. Central to the recent controversy are the relative roles of liquidity and counterparty (credit) risk in explaining the size and dynamics of various money market spreads and the term structure of the spreads. Understanding what are the major driving forces behind the evolution of money market spreads has important implications for central bank policy, which is likely to be more effective in addressing liquidity problems (e.g. via LOLR intervention) than for addressing solvency issues (which should be addressed by the fiscal authorities).

Our contribution to the ongoing debate on the dynamics of money market spreads is empirical and is motivated by the "shocking" evidence of non-stationary behaviour of money market spreads. In fact, in our view, empirical work testing the effectiveness of central bank policies has largely overlooked the complexity of the market environment and its implications for the statistical properties of the data. Thus, our main goal is to carefully document the "fingerprint" of money market turbulence. However, our econometric framework allows incorporating policy interventions and is thus well suited also for testing their impact whilst carefully accounting for the non-stationary properties of the data.

The remainder of the paper is structured as follows. Section 2 presents the data and reviews the economics of money market spreads in the euro area. Section 3 presents the econometric methodology. Section 4 reports the econometric results on persistency and Section 5 on copersistency. The global dimension of the crisis is illustrated in Section 6. Impulse-response analysis and error variance decomposition are presented in Section 7. Section 8 concludes.

2 Data and modelling issues

The EURIBOR-OIS spread is a measure of stress in the euro area interbank market, and reflects three inter-related factors: 1) liquidity risk; 2) credit / counterparty risk; and 3) investor sentiment / risk appetite / uncertainty. The EURIBOR, or Euro Interbank Offered Rate, is an average interbank lending rate obtained from inquiring a panel of large banks at which rate they would be willing to offer funds to highly rated banks. Thus, EURIBOR rates are reference rates for uncollaterized lending in Euro. Note that there must not be any effective transaction among banks associated with the reference rates. Indeed, after August 2007 market participants reported that there were virtually no funds offered among banks at term maturities; however, EURIBOR quotes have never been discontinued. This is probably due to the
fact that these rates provide indexing for lending by banks to households and firms and for derivatives contracts (e.g. interest rate futures and options). The EONIA, or Euro Over Night Index Average, is a quantity weighted average of the rates applied to uncollateralized overnight lending by a panel of large Euro area banks. Thus, the EONIA represents rates with underlying traded volumes. Overnight Index Swaps (OIS) are the fixed rates of swaps contracts for various maturities, whereby one party to the contract pays the fixed rate and in exchange receives the average EONIA over the maturity of the contract. In a swap contract there is no exchange of principal which mitigates counterparty risk. If one party to the contract defaults there is interest rate risk that needs to be covered until the remaining maturity, but there is no pecuniary loss due to default.

Both EURIBOR and OIS rates incorporate expectations of the average overnight rate until maturity; these expectations cancel out when one computes the EURIBOR-OIS (EE) spread using rates of the same maturity. If the resulting spreads are different from zero it certainly must be because of counterparty risk, which is priced in the EURIBOR rate but not in the OIS rate. However, consider for example a three-month OIS contract; a bank with access to the overnight interbank market can borrow daily for three months covering the interest rate risk by paying the fixed leg of the swap contact and receiving the average variable EONIA. The bank will prefer this option to the alternative of borrowing unsecured at EURIBOR if the latter rate is at a large spread against the OIS; if a large number of banks follows this strategy the OIS rate will tend to increase narrowing the spread. Nevertheless, this strategy presupposes that the bank will always be able to borrow the needed funds in the overnight interbank market, exposing the bank to the risk that such liquidity may not be available every day for the next three months. Moreover, relying exclusively on the overnight interbank market for funding longer-term assets leads to an extreme maturity mismatch exposing the bank to the liquidity risk embedded in such maturity transformation. Thus, liquidity risk may, after all, prevent the convergence between the OIS rate and the EURIBOR rate. The EURIBOR-OIS (EE) spread may reflect liquidity risk due to a different channel which is liquidity hoarding when, faced with large uncertainty about the valuation of their own assets and the availability of longer-term funding leads banks to build up "excess reserves". In addition to these factors EURIBOR-OIS spreads may reflect swings in investor sentiment (e.g. variation in risk appetite). Moreover, in the context of a systemic banking crisis it is very difficult to distinguish financial institutions that are "only" liquidity constrained from those that are insolvent, due to the chain of derivatives contracts and the opacity of interbank linkages. For all these reasons we consider the various EONIA-OIS spreads as
measures of money market stress reflecting the complex interaction between liquidity risk, credit risk and variation in risk appetite.

The sample covered in the econometric analysis runs from 20 June 2005 until 7 April 2009, for a total of 992 working days. The data set is composed of fifteen EURIBOR-OIS interest rate spreads (EE thereafter), from the 1-week maturity \( w^{1w}_t \) to the 1-year maturity \( w^{12m}_t \). The data is of daily frequency and its source is REUTERS.

As shown in Figure 1 (top plots), EE dynamics are telling concerning the size and development of the financial crisis. Two waves of increasing stress can be detected in the interbank market since the beginning of the crisis. The beginning of the first wave is on 9 August 2007, i.e. the day the French bank BNP Paribas revealed its inability to value structured products for three of its investment funds.\(^1\) The crisis triggered interventions by the European Central Bank and the US Federal Reserve, injecting overnight funds of euro 130 billion and US$ 24 billion, respectively, on 9 August 2007. Additional provisions were taken by the US Federal Reserve a few days later.\(^2\) The interbank market stress was indeed sizable, with the average spread moving from a range of 3b.p. (1-week) to 7b.p. (1-year), to a range of 15b.p. to 74b.p. until 15 September 2008.\(^3\) Since September 16, the day after of Lehman Brothers bankruptcy, which can be taken as the starting day for the second wave of magnified money market stress, the spreads climbed rapidly, to reach maximum values in the range of 100b.p. to 233b.p. between October 8 and October 13, according to maturity (sample average values after the second wave of stress are in the range 28b.p. to 155b.p.). In the face of major difficulties in the banking sector in the US and Europe, various forms of liquidity injection and unconventional monetary policy measures were taken by central banks, aiming at defreezing the interbank and credit markets, and

\(^1\)While panic set in in August 2007, the US subprime crisis had already been mounting at least since the beginning of 2007, when the 2007-01 BBB- ABX index fell abruptly below par (to about 80) after issuance. The following issue, i.e. the 2007-02 BBB- ABX index, even started trading below par at about 60, evidencing the difficulty in pricing sub-prime risk. Major drops then occurred in August (to 40) and October (to 20) 2007. ABX index price decline has continued through 2008, trading in October 2008 at a value of about 5. Panic was determined by uncertainty concerning the value of the sub-prime collateral. The information problem then translated into uncertainty concerning the value of any structured product offered as collateral in repo transactions, not just residential mortgage-backed securities (RMBS), leading to the freezing of the repo markets.

\(^2\)A Federal funds rate cut of 50 b.p. was implemented on 17 August 2007. Additional Fed funds rate cuts were implemented in September 18, 2007 (50 b.p.) and October 31, 2007 (25 b.p.).

\(^3\)See ECB (2007) and Ferguson at al. (2007) for an early assessment of the US sub-prime credit crisis.
easing the banking sector from the burden of unperforming loans, as well as to facilitate its recapitalization which has been supported by the intervention of the governments.\footnote{The Senate of the US Congress passed the Emergency Economic Stabilization Act on October 1 2008, while the House on October 3 2008. On the same day President Bush signed the bill into law. A US$ 700 billion Troubled Assets Relief Program was then made available to relieve banks from unperforming loans and bad assets. Following the US, also the UK and Euro Area governments launched similar rescue plans. Major banks benefited from direct capital injection by the government, against the acquisition of stakes: Royal Bank of Scotland, Lloyds TSB, Halifax Bank of Scotland in the UK; Goldman Sachs, Morgan Stanley, JP Morgan Chase, Bank of America, Citigroup, Wells Fargo, Bank of New York, Mellon, and State Street in the US; Unicredit, Intesa-San Paolo and Monte dei Paschi di Siena in Italy; UBS and Credit Suisse in Switzerland.} Starting from 9 October 2008, spreads have progressively narrowed, albeit with different speeds across maturities, i.e. at a quicker pace the shorter than the longer maturities. In particular, while the 1-week maturity has rapidly attained the pre-Lehman Brothers bankruptcy average values since December 2008, it has taken much longer for the other maturities to adjust. In April 2009 (end of our sample period), only the two-week spread has reverted to the pre-Lehman Brothers bankruptcy average value (since 11 February 11), and the three-week spread being very close to it at the end of the sample. Differently, for the one-year rate the distance from the average value at the end of sample is close to 20b.p.:

Not only the level of the spreads, but also their volatility seems to have been affected by the crisis. From Figure 1 (bottom plots) large changes in spread volatility can be noted, from standard deviation values in the range 1.0b.p. to 1.5b.p., across maturities, over the pre-turmoil period, to a range of 9b.p. to 19b.p. over the first stress wave period, and to a range of 20b.p. to 45b.p. over the second stress wave period. Hence, there also appear to be a close and positive association between the level and the volatility of the spreads not only concerning the direction of change (increasing across crisis regimes), but also concerning the timing of change (changes in level and volatility are temporally coordinated). The 20-day moving standard deviations plotted in Figure 1 (bottom plots) show similar dynamics relative to the spreads in levels. In particular, with reference to the end of the sample, a similar progressive reduction in levels and volatility towards first stress wave’s overall levels can be noted.

Overall, the evidence suggests that markets have almost overcome the second wave of stress, but are still fairly apart from pre-crisis values. Indeed, this finding is fully consistent with the evidence that the financial crisis spilled over to the real economy since the fourth quarter of 2008.
3 Econometric methodology

In our empirical analysis, we jointly model the dynamics of the EE interest rate spreads \((x_t)\) according to the following fractionally integrated factor vector autoregressive (FI-F-VAR) model

\[
\begin{align*}
    x_t &= \Xi z_t + \Lambda \mu t + \Lambda f f_t + C(L)(x_{t-1} - \Lambda \mu t_{-1}) + v_t \\
    v_t &\sim \text{iid}(0, \Sigma_v) \\
    D(L)f_t &= \eta_t = \sqrt{h_t}\psi_t, \\
    \psi_t &\sim \text{iid}(0, I) \\
    M(L)(h_t - w_t) &= [M(L) - N(L)]\eta_t^2
\end{align*}
\]

where \(x_t\) is a \(n\)-variate vector of long memory processes subject to structural breaks\(^5\), \(f_t\) is a \(r\)-variate vector of heteroskedastic long memory (in mean \((d)\) and variance \((b)\)) factors \((0 < d_i < 1, 0 < b_i < 1, i = 1, ..., r)\), \(\mu_t\) is an \(m\)-variate vector of common break processes, \(z_t\) is a \(q\)-variate vector of exogenous/policy variables, with parameters collected in the \(n \times q\) matrix \(\Xi\), \(v_t\) is a \(n\)-variate vector of zero mean idiosyncratic i.i.d. shocks, with covariance matrix \(\Sigma_v = \text{diag}\{\sigma_1^2, \sigma_2^2, ..., \sigma_r^2\}\), \(\psi_t\) is a \(r\)-variate vector of common zero mean i.i.d. shocks, with covariance matrix \(\Sigma_{\psi} = I_r\), \(E[\psi_i v_j s] = 0\) all \(i, j, t, s\), \(\Lambda_f\) and \(\Lambda_\mu\) are \(n \times r\) and \(n \times m\), respectively, matrices of loadings, \(C(L)\) is a finite order stationary matrix of polynomials in the lag operator, i.e. \(C(L) = C_1 + C_2 L^2 + ... + C_r L^r\), \(C_{j j} = 1, ..., \) is a square matrix of coefficients of order \(n\),

\[
D(L) = \text{diag}\{(1 - L)^{d_1}, (1 - L)^{d_2}, ..., (1 - L)^{d_r}\}
\]

\[
M(L) = \text{diag}\{(1 - \beta_1 L), (1 - \beta_2 L), ..., (1 - \beta_r L)\}
\]

and

\[
N(L) = \text{diag}\{\phi_1 L(1 - L)^{b_1}, \phi_2 L(1 - L)^{b_2}, ..., \phi_r L(1 - L)^{b_r}\}
\]

are diagonal stationary polynomial matrices in the lag operator of order \(r\). Hence, \(h_t\) is the time dependent \(r\)-variate conditional variance vector process, defined as \(h_t = \text{Var}(f_t|\Omega_{t-1})\), following the A-FIGARCH\((1, d, 1)\) process of Baillie and Morana (2009), where \(w_t\) is the long-term conditional variance process or the break in variance process. Non negativity constraints, involving \(x\) the \(\beta_i\), \(\phi_i\), and \(b_i\) parameters, for well defined conditional variance processes are discussed in Baillie and Morana (2009) and imposed in estimation following the exponential specification of Engle and Rangel (2008). The

\(^5\)See Baillie (1996) for an introduction to long memory processes.
long memory factors $f_t$, are also assumed to be conditionally orthogonal, i.e.
$q_{f,t} = \text{Cov}(f_{i,t}, f_{j,s}| \Omega_{t-1}) = 0$ all $i, j, t, s$.

### 3.1 The reduced fractional VAR form

By taking into account the binomial expansion in (2) and substituting (2) into (1), the infinite order vector autoregressive representation for the factors $f_t$ and the series $x_t$ can be written as

$$
\begin{bmatrix}
  f_t \\
  x_t - \Lambda_\mu t_t
\end{bmatrix} =
\begin{bmatrix}
  0 \\
  \Xi
\end{bmatrix} z_t +
\begin{bmatrix}
  \Phi(L) & 0 \\
  \Phi^*(L) & C(L)
\end{bmatrix}
\begin{bmatrix}
  f_{t-1} \\
  x_{t-1} - \Lambda_\mu t_{t-1}
\end{bmatrix}
\begin{bmatrix}
  \varepsilon_{f,t} \\
  \varepsilon_{x,t}
\end{bmatrix},
$$

where $\Phi^*(L) = \Lambda_f \Phi(L)$, $D(L) = I - \Phi(L)L$, $\Phi(L) = \Phi_0 L^0 + \Phi_1 L^1 + \Phi_2 L^2 + \ldots$, $\Phi_i, \forall i$, is a square matrix of coefficients of dimension $r$,

$$
\begin{bmatrix}
  \eta_t \\
  \varepsilon_t
\end{bmatrix} =
\begin{bmatrix}
  I \\
  \Lambda_f
\end{bmatrix} \sqrt{h_t \psi_t} +
\begin{bmatrix}
  0 \\
  v_t
\end{bmatrix}.
$$

### 3.2 Estimation

Since the infinite order representation cannot be handled in estimation, a truncation to a suitable large lag for the polynomial matrix $\Phi(L)$ is required. Hence, $\Phi(L) = \sum_{j=0}^p \Phi_j L^j$. Then, estimation can be implemented following an iterative procedure consisting of the following steps.

- **Step 1: persistence analysis.** Long memory and structural break tests are carried out on the series of interest in order to determine their persistence properties. Several approaches are available in the literature for structural break testing and estimation, as well as for long memory parameter estimation. See the Section on persistence properties for details.

- **Step 2: initialization.** Conditional on the presence of structural breaks and long memory in the series investigated, an initial estimate of the unobserved common deterministic and long memory factors can be obtained by decomposing the series into their break process ($b_t$) and long memory components ($l_t$), i.e. $x_t = b_t + l_t$.

  Then, the common break processes are estimated by means of Principal Components Analysis (PCA) implemented using the estimated break process $\hat{b}_t$, yielding an estimate of the $m \times 1$ vector of the standardized
(\hat{\Sigma}_b = I_m) principal components or common break processes \( \hat{\mu}_t = \hat{\Lambda}_b^{-1/2} \hat{A} \hat{b}_t \), where \( \hat{\Lambda}_b \) is the diagonal matrix of the estimated non zero eigenvalues of the reduced rank variance-covariance matrix of the (estimated) break processes \( \hat{\Sigma}_b \) (rank \( m < n \)) and \( \hat{A} \) is the matrix of the associated orthogonal eigenvectors.

Next, the common long memory components can be obtained by means of PCA implemented using the estimated break-free processes \( bf_t = x_t - \hat{b}_t \), yielding the estimate of the \( r \) common long memory factors \( \hat{f}_t = \hat{\Lambda}_{bf}^{-1/2} \hat{B}^{bf}_t \), where \( \hat{B}^{bf} \) is the matrix of the estimated orthogonal eigenvectors associated with the \( r \) non-zero eigenvalues of the reduced rank variance-covariance matrix of the (estimated) break-free processes \( \hat{\Sigma}_{bf} \) (rank \( r < n \)).

**Step 3: starting the iterative procedure.** Conditional on the estimate of the fractional differencing parameter, the lag truncation order, and the estimate of the deterministic and stochastic factors, the iterative estimation procedure is started by computing preliminary estimates of the matrix \( \Xi \), the polynomial matrix \( C(L) \) and the \( \Lambda_f \) factor loading matrix, by means of OLS estimation of the equation system in (1).

Then, a new estimate of the \( m \) deterministic factors can be obtained from the first \( m \) principal components of the long memory-free series \( \left[ I - \hat{C}(L)L \right] [x_t - \hat{\Lambda}_\mu \hat{\mu}_t] + \hat{b}_t^- \), where \( \hat{b}_t^- \) is the previous round estimate of the break process component.

Next, conditional on the new deterministic factors and factor loading matrix (\( \hat{\Lambda}_\mu = \hat{A} \hat{\Lambda}_b^{1/2} \)), the new stochastic common factors can be obtained as the first \( r \) principal components of the set of break-free processes \( x_t - \hat{\Lambda}_\mu \hat{\mu}_t \), and new estimates for the \( C(L) \) polynomial matrix and the \( \Lambda_f \) factor loading matrix can also be obtained by means of OLS estimation of the equation system in (1).

The procedure described in step 3 is then iterated until convergence.

**Step 4: restricted estimation of the full model.** Once the final estimates of \( f_t \) and \( \mu_t \) are available, by employing the estimate of the \( \Phi(L) \) matrix and the final estimates of the \( \Xi \), \( \Lambda_f \), \( \hat{\Lambda}_\mu \) and \( C(L) \) matrices, the restricted VAR in (3) can be estimated. Following the thick modelling strategy of Granger and Jeon (2004), median estimates of the parameters of interest, and confidence intervals robust to model misspecification, can be obtained by means of simulation methods. We remind to Cassola and Morana (2009), Morana (2009) and Beltratti and Morana (in press) for details concerning the identification of the common and idiosyncratic shocks, which can be performed by means of a double Choleski approach, and the computation of impulse response functions and forecast error decomposition.
• **Step 5: conditional variance analysis.** Median factor estimated residuals can be firstly computed using the estimated median \( (me) \) parameters, i.e.

\[
\hat{\eta}_t = \hat{f}_t - \hat{\Phi}(L)^{(me)} \hat{f}_{t-1}
\]

Then, an A-FIGARCH version of the O-GARCH model of Alexander and Chibumba (1997) is implemented. The latter consists of the following steps. Firstly, the model is estimated for each of the factor residual series and the conditional variance process computed \( (h_t) \). Secondly, consistent with the assumptions of conditional and unconditional orthogonality of the factors, the conditional variance \( (H_{x,t}) \) and correlation \( (R_{x,t}) \) matrices for the actual series may be computed as

\[
H_{x,t} = \Lambda_f H_1 \Lambda_f',
\]

where \( H_t = \text{diag} \{ h_{1,t}, h_{2,t}, ..., h_{r,t} \} \), and

\[
R_{x,t} = H_{x,t}^{-1/2} H_{x,t}^{*} H_{x,t}^{-1/2},
\]

where \( H_{x,t}^{*} = \text{diag} \{ h_{x1,t}, h_{x2,t}, ..., h_{xn,t} \} \), respectively.

### 3.2.1 Asymptotic properties

Recent theoretical results validate the use of PCA in the case of both weakly (Bai, 2003) and strongly (Bai, 2004; Bai and Ng, 2004) dependent processes. In particular, Bai (2003) establishes consistency and asymptotic normality of PCA when both the unobserved factors and the idiosyncratic components show limited serial correlation, and the latter also display heteroscedasticity in both their time-series and cross-sectional dimensions. In Bai (2004) the above results (consistency and asymptotic normality) are extended to the case of I(1) unobserved factors and I(0) idiosyncratic components, also allowing for heteroscedasticity in both the time-series and cross-sectional dimensions of the latter component. Moreover, Bai and Ng (2004) have established consistency also for the case of I(1) idiosyncratic components. As pointed out by Bai and Ng (2004), consistent estimation should also be achieved by principal components techniques in the intermediate case of long-memory processes, and Monte Carlo results reported in Morana (2007) provide supporting small (cross-sectional) sample empirical evidence for PCA in the latter framework. Finally, PCA based estimation of common non linear deterministic components from a set of estimated individual non linear deterministic components has also been advocated by Bierens(2000).⁶

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⁶Yet, details cannot be found in the published version of his paper.
The proposed estimation procedure is multi-step, but iterated to improve
efficiency, based on the use of consistent and asymptotically normal estima-
tors of the fractional differencing parameter (semiparametric or parametric
estimators) and the weakly dependent part of the model (the OLS estimator).
Moreover, the model could also be estimated without fractional prefiltering,
by relying on the infinite order VAR representation of the VARFIMA struc-
ture of the $D(L)$ matrix, leading to standard stationary polynomials in the
lag operator, with all the roots outside the unite circle.

Although a formal proof is beyond the scope of this paper, it is conjec-
tured, therefore, that the proposed estimation procedure leads at least to
consistent estimation of the parameters and quantities of interest.

4 Persistence properties

The large and persistent changes in the mean and volatility levels of the
spreads are indicative of structural breaks in their mean and variance com-
ponents. As, in addition to breaks, other forms of persistence are plausible,
i.e. long memory or stochastic persistence, a modelling framework allowing
to account for both features, and to distinguish among them, should be em-
ployed. The Dolado et al. (2004) structural break test (DGM test), modified
to account for a general and unknown structural break process (Morana,
2007b), has therefore been employed in order to assess the source of per-
sistence in the investigated series. Moreover, also the Bai and Perron (BP,
1998) test has been employed in order to gauge evidence on the number
and location of break points. On the other hand, the Moulines and Soulier
(1999) broad band log periodogram estimator has been employed to assess
the degree of fractional integration of the actual and break-free EE spreads.

\footnote{In some cases also asymptotically efficient.}

\footnote{The Moulines and Soulier (1999) broad band log periodogram estimator yields an
estimate of the fractional differencing parameter ($d$) from OLS estimation of the regres-
sion $\ln(\exp^{-\psi(m)} \sum_{j=1}^{n_m} I_n(\lambda_j)) = d(-2 \log \lambda_k) + \sum_{i=0}^{p} [\gamma_i \frac{\cos(\lambda \lambda_k)}{\sqrt{\pi}}] + e$, where $\lambda_j = 2\pi j/n_m$, $j = 1, \ldots, n/2$, $m$ is the size of the nonoverlapping blocks for periodogram ($I_n(\lambda_j)$) av-
eraging, $n_m = 2m [n/2m]$, $K_n = n/2m$, $k = 1, \ldots, K_n$, $J_n = \{m(k-1)+1, \ldots, mk\}$, $\lambda_k = (2k-1)\pi/2K_n$, $\psi(m)$ is the digamma function. Under some conditions it follows
that $\sqrt{\frac{1}{p}} \left( \hat{d}_{p,n,m} - d \right) \overset{d}{\rightarrow} N(0, m\psi'(m))$. The order of the cosine expansion is determined
by means of Mallow’s $C_L$ criterion, while a choice of $m = 4$ is suggested in Moulines and
Soulier (1999).}
4.1 Methodological details

The results of the BP tests are reported in Table 1, Panel A. As is shown in the Table, the evidence points to two break points with similar location across maturities, occurring between August 9 and August 16 2007 the former, and on September 16 2008 the latter. Hence, the selected break points can be related to the starting days of the two stress waves, i.e. August 9 2007 and September 16 2008.\footnote{It is September 16 2008, rather than September 15 2008, the starting day of the second wave of panic for Europe, due to lagged markets opening effects.} Very large absolute and relative increase in the mean of the spreads, i.e. in the range 48\% to 255\%, according to maturity (88\% on average across maturities), and 9\% to 32\% (16\% on average across maturities), can be noted for the selected dates, respectively. For some of the maturities, i.e. starting from the 8-month maturity onwards, the evidence (not reported) would actually point to an additional break point, occurring on February 19 2008. Yet, the latter is likely to be explained by a change in slope in the dynamic path of the EE spreads, which the BP modelling strategy does not allow to account directly. Yet, December 5 2008, could be selected as additional break point, and associated with the 75b.p. cut announced on December 4 2008 by the ECB and implemented on the following day. In addition to a sizeable contraction in the EE spreads, in the range -11\% to -31\% (-16\% on average), also a reversal in the EE spreads trend can be observed. Starting with December 5 2008, spreads have steadily decreased, converging towards first stress wave-levels. As the minimum regime length is fixed at 0.15T, the significance of the suggested additional break point could not be tested by means of the BP test. Implementation within the DGM testing framework, however, suggest that the additional selected break point, as well as the changing slope structure, is appropriate for the data investigated (results are discussed below).

Hence, concerning the structure of the candidate break process three modelling strategies have been implemented. The first strategy allows for an abrupt change in the level of the modelled variables (dummy model, DM). The break points have been selected according to the BP test, also allowing, after additional testing (using the DGM test), for a changing slope structure and for a break occurring on December 5 2008. Moreover, a flexible Fourier functional form (Gallant, 1984; FFM) and a cubic spline smoother (CSM) approach have also been employed. The latter methods do not require any assumption on the exact timing and number of break points (see Enders and Lee, 2004; Baillie and Morana, 2008, 2009; Engle and Rangel, 2008), allowing for a smooth transition across regimes, as well as for a time-varying mean level within each regime. A dummy model with smooth (spline) transitions
across regimes (DCSM) has finally been employed. The latter model allows for additional flexibility relatively to the standard dummy model, and it seems particularly suited for the data at hand, where relatively large changes in the level of the variables occur consecutively in the range of few days, rather than in just a single day. Also in the spline-dummy specification a broken trend component has been included, in order to model slope effects featuring the intermediate to long hand of the risk term structure. Experimentation with an additional break point, set on December 5 2008, has also been carried out.

In addition to the mean component, also the volatility component has been assessed for structural breaks by means of the BP test, using the absolute first difference of the spreads as volatility proxy. While, the increase in long-term volatility triggered by the setting in of the crisis and the spreading of the first stress wave is undisputable, less clear-cut is whether a further increase in long-term volatility occurred following the spreading of the second stress wave. As is shown in the Table, the location of the break points would be similar to what found for the mean of the process, with breaks occurring around August 9 2007 and September 16 2008. Yet, the selection of the latter break point is not robust to the selection method employed.\footnote{The modified BIC criterion (LWZ) points to a single break point occurring on August 9 2007 for all the series, apart from maturities between the two-month and seven-month horizon. The results are available upon request from the authors.} Hence, a single break point, i.e. August 9 2007, has been retained for the rest of the analysis.

Hence, the following break process specifications have been employed:

\[
bp_t = \begin{cases} 
\alpha_0 + \alpha_1 D_{1,t} + \alpha_2 D_{2,t} + \alpha_3 D_{3,t} + \alpha_4 D_{4,t} \\
\alpha_0 + \alpha_1 t + \alpha_2 t^2 + \alpha_3 t^3 + \sum_{j=1}^{K} [\gamma_j \sin(2\pi j t/T) + \delta_j \cos(2\pi j t/T)] \\
f_p(t) \\
(\alpha_0 + \alpha_1 D_{1,t} + \alpha_2 D_{2,t} + \alpha_3 D_{3,t} + \alpha_4 D_{4,t}) \cup f_p(t)
\end{cases}
\]

where \( t = 1, \ldots, T, \ T = 992 \), \( D_1 \) is a step dummy variable with unity value over the period August 9 2007 to April 7 2009 included, \( D_2 \) is a step dummy variable with unity value over the period September 16 2008 to April 7 2009 included, \( D_3 \) is a broken linear trend variable, with non-zero values over the period December 5 2008 to April 7 2009 included, \( D_4 \) is a broken linear trend variable, with non-zero values over the period September 16 2008 to December 5 2008 included, \( K \) is the order of the trigonometric expansion of the Fourier flexible functional form, while the objective function for the
determination of the smoothing parameter \( p \) for the spline specification is

\[
S(p) = p \sum_t (x_t - f(l_t))^2 + (1 - p) \int f''(l_t)^2,
\]

where \( x_t \) is the generic interest rate spread to be smoothed, \( l_t \) defines the position of knots, \( \int f''(t) \) is the integrated squared second derivative of the cubic spline function \( f(l) = a_i + b_i l + c_i l^2 + d_i l^3 \). See Silverman (1985) for details on estimation. Differently, for DM and FFM OLS estimation is performed, while DCSM requires a two-step procedure, i.e. the application of OLS estimation first and then spline smoothing in the neighborhood of the break points in the estimated dummy break process.

The DGM test is implemented by means of the Dickey-Fuller type auxiliary regression

\[
\Delta^d y_t = \Delta^d b p_t^* - \phi b p_{t-1}^* + \phi y_{t-1} + \sum_{j=1}^s \Delta^d y_{t-j} + v_t, \tag{7}
\]

where \( b p_t^* \) is the estimated candidate break process from any of the three models employed, \( v_t \sim iid(0, \sigma^2_{\varepsilon,t}) \). The null hypothesis of \( I(d) \), i.e. pure long memory, implies \( \phi = 0 \), while the alternative of \( I(0) \) stationarity plus structural change implies \( \phi < 0 \). Critical values have been computed, case by case, by means of simulation assuming two scenarios for the long memory process \( \phi(L)(1-L)^d y_t = \varepsilon_t, \varepsilon_t \sim iid(0, \sigma^2_{\varepsilon,t}) \) under the null. The first scenario (I) assumes that \( \sigma^2_{\varepsilon,t} = \sigma^2_{\varepsilon,1}, t = 1, ..., 992 \), i.e. unconditional homoscedasticity. On the other hand, the second scenario (II) assumes unconditional heteroscedasticity, with \( \sigma^2_{\varepsilon,t} = \sigma^2_{\varepsilon,1}, t = 1 (20/06/05), ..., 588 (08/08/07) \) and \( \sigma^2_{\varepsilon,t} = \sigma^2_{\varepsilon,2}, t = 589 (09/08/07), ..., 992 (07/04/09) \). The values of the parameter employed in the simulations were set according to the properties shown by the investigated series. The lag order \( s \) in the auxiliary specification was finally selected by means of the AIC criterion, allowing for up to five lags.

### 4.2 Results for the DM and DCSM specifications

In Table 1, Panel A and Panel B, the results of the persistence analysis are reported\(^\text{11}\). According to the BBLP estimator (Panel B), strong (non stationary) long memory can be found in the actual EE spreads, with an

\(^{11}\) Due to the potential break in the unconditional variance of the EE spreads, the estimates of the long memory parameter for the break-free series are obtained from standardized processes, using sample mean and variance estimates over three periods, i.e. 20/06/05 to 08/08/07, 09/08/07 to 15/09/08, and 16/09/08 to 07/04/09.
average estimated fractional differencing parameter of about 0.94 (0.041). A Bonferroni bounds test does not allow to reject the null of equal fractional differencing parameter across EE spreads for the actual series (the minimal p-value across the 110 possible bivariate tests is 0.002, to be compared with a 5% critical value equal to 5E-4). Sizable long memory can also be found in the break-free series yield by the DM and DCSM specifications (in the range 0.24 to 0.64, about 0.40 (0.041) on average), with persistence increasing with maturity up to the three-week horizon and then decreasing thereafter. A Bonferroni bounds joint test yields clear-cut rejection of the null of equal fractional differencing parameter for the break-free series across all the maturities, the latter results being actually due to the strongest persistence of the shortest end of the term structure than the longest end, while similar persistence can be found for consecutive maturities.

The finding of significant long memory in both the actual and break-free specifications points to non spurious structural change in the EE spreads, as, otherwise, evidence of overdifferencing, i.e. a negative estimate for the fractional differencing parameter, would be expected (see Granger and Hyung, 2004). The DGM test supports the latter conclusion, pointing to significant break processes for all of the EE spreads, as the null of pure long memory process is rejected in all of the cases (both DM and DCSM), at the 5% significance level (a zero lag order (s = 0) was the selected optimal order by the AIC criterion for the DGM auxiliary equation).

Evidence of significant instability can also be detected in the estimated persistence parameter, when computed separately for the pre-crisis and crisis period (Table 1, Panel B). The null of temporal stability is in fact strongly rejected both using a Bonferroni bounds joint test (the p-value is 1E-10 in both cases) and maturity by maturity pairwise comparison.

It may be concluded that most of the non stationarity in the actual EE spreads may be associated with effects of the two stress waves in the inter-bank market. As the break process describes the long-term evolution of the spreads, the findings point to long lasting (permanent) effects of the current crisis on the structure underlying credit/liquidity risk. Deviations from the long-term values measured by the break process would tend to be corrected, albeit, due to their long memory feature, not instantaneously. Consistent, due to the long memory feature, reductions in the EE spreads, even to precrisis levels, might take place (temporarily) also without a full resolution of banking stress. Yet, only the solution of the crisis, could make long-lasting (permanent) the reversion to precrisis levels in credit/liquidity risk.
4.3 Results for the FFM and CSM specifications

Given the results provided by the BBLP estimator and the DGM test for the DM specification, the order of the flexible Fourier function and the smoothing parameter for the cubic spline smoother have been selected, across possible values, in order to minimize the root mean square error distance of the estimated break processes from the dummy break process specification. Following the latter criterion, a seventh order specification has then been selected for the FFM specification, while the smoothing parameter has been set equal to 1e-05 for the CSM specification.

In Figure 2 the estimated break process obtained from the two latter methods are contrasted with the estimated dummy break processes for the shortest and longest maturities in the sample. As is shown in the plot, all the methods yield similar estimates of the candidate break processes, with, FFM and CSM implying a smoother transition across regimes.

Coherent, sizable long memory can also be detected in the FFM and CSM break-free series, in the range 0.51 to 0.75 (FFM, 0.66(0.041) on average) and 0.49 to 0.75 (CSM, about 0.62(0.041) on average). Again, a Bonferroni bounds joint test allows to reject the null of equal fractional differencing parameter for the break-free series across all the maturities also for the FFM and CSM specifications, also pointing to stronger persistence at the shortest end of the risk term structure than at the longest end. Yet, by comparing the average values obtained from the various methods, it can be concluded that the degree of persistence is significantly larger for the trigonometric and spline models than for the dummy ones. The finding, may be explained by the smoother transition across regimes shown by the FFM and CSM models, probably not appropriate to capturing the turmoil that quickly spreads across financial markets, following the release of key news on August 8 2007 and September 15 2008. Coherently, the evidence of significant structural change for all the maturities is weaker for FFM (which shows the slowest transition), and only slightly so for CSM, than for the DM and DCSM models. Similarly, weaker evidence of instability can be detected for the persistence parameter, which does not appear to be statistically different across regimes, using a Bonferroni bounds joint test (the p-values of the test are equal to 0.012, and 0.004, for FFM and CSM, respectively). A similar conclusion can be achieved by considering each maturity at the time (1% level, apart for the 1-week spread, using CSM).
5 Copersistence properties

As the source of persistence of the EE spread is explained by both structural breaks (in the mean of the process) and stationary, and temporally stable, long memory, up to two persistence features can be shared across maturities, i.e. common break processes and common long memory factors. In order to assess the presence of commonalities in the EE spreads, principal components analysis (PCA) has then been employed. The use of the latter is motivated by recent theoretical and empirical results concerning the application of PCA for strongly persistent processes.\textsuperscript{12}

As shown in Table 2, Panel A, indeed strong evidence of commonalities can be detected on the actual EE interest rate spreads. In fact, a single principal component explains about 99% of total variance, accounting also for over 95% of the variance of each of the EE spreads from the 2-week maturity onwards.

5.1 Cobreaking and common long memory factor analysis

Once principal components analysis is carried out by isolating the break process component from the long memory component, further insights on the source of idiosyncratic dynamics at the shortest end of the term structure of the EE spreads can be gauged. In fact, as shown in Table 2, Panel A, independently of the break process modelling strategy implemented, over 99% of total variance for the break process components is explained by the first principal component. The latter also accounts for over 95% of the variability.

\textsuperscript{12}Recent theoretical results validate the use of PCA in the case of both weakly (Bai, 2003) and strongly (Bai, 2004; Bai and Ng, 2004) dependent processes. In particular, Bai (2003) establishes consistency and asymptotic normality of PCA when both the unobserved factors and the idiosyncratic components show limited serial correlation, and the latter also display heteroscedasticity in both their time-series and cross-sectional dimensions. In Bai (2004) the above results (consistency and asymptotic normality) are extended to the case of I(1) unobserved factors and I(0) idiosyncratic components, also allowing for heteroscedasticity in both the time-series and cross-sectional dimensions of the latter component. Moreover, Bai and Ng (2004) have established consistency also for the case of I(1) idiosyncratic components. As pointed out by Bai and Ng (2004), consistent estimation should also be achieved by principal components techniques in the intermediate case of long-memory processes, and Monte Carlo results reported in Morana (2007) provide supporting small (cross-sectional) sample empirical evidence for PCA in the latter framework. Finally, PCA based estimation of common non linear deterministic components from a set of estimated individual non linear deterministic components has also been advocated by Bierens (2000), albeit no details can be found in the published version of the paper.
of the break process for each of the maturities, apart from the shortest one. Yet, also for the latter the proportion of explained variance is never lower than about 90%.

A different picture is provided by the long memory components. For the latter, the first principal component accounts for about 65% for the DM and DCSM models, and about 80% for the FFM and CSM models. Independently of the break process modelling strategy, the strongly idiosyncratic properties of the shortest end of the EE spreads term structure is a clear-cut finding, albeit some differences can be noted across the two categories of break-free series, with the DM and DCSM series featuring more idiosyncratic than the FFM and CSM series. In fact, for the DM and DCSM series it is the second principal components to account for the largest proportion of variance for maturities within 1-month (41% to 63%), while for the FFM and CSM series it is first principal components to dominate, also at the shortest end of the term structure (26% to 78% within 1-month). Jointly, the first two principal components account for about 95% of total variance for the FFM and CSM models, and for about 84% for the DM and DCSM models, capturing interesting commonalities across spreads. Differently, independently of the break modelling strategy, higher order principal components mainly capture idiosyncratic features. In terms of persistence properties, as shown in Table 3, Panel A, independently of the break modelling procedure, all the relevant principal components show the long memory feature, with estimated fractional differencing parameters consistent with the findings for the break-free series. In fact, the estimated fractional differencing parameters are in the range 0.32 to 0.70, 0.510(0.041) on average. Yet, some interesting differences can be noted for the two categories of models, i.e. the dummy models (DM and DCSM) on the one hand, and the flexible/spline models (FFM and CSM) on the other hand. In fact, while for the former category of models the second factor (the one closely associated with the shortest end of the risk structure) is the most persistent one, the opposite can be noted for the second category of models. Given the persistence properties shown by the break-free series (the shortest maturities being more persistent than the longest ones), it can be concluded that the common long memory factors extracted from the DM and DCSM break-free series are more likely to offer an accurate description of the persistent dynamics in risk spreads.

As shown in Figure 3, an increase in persistence can be noted following August 9 2007 (observations 559) as the common long memory factors appear to be much smoother than before. Separate estimation of the fractional differencing parameter over the precrisis and crisis samples yields the estimates reported in Table 3, Panel A. As can be noted from the Table, the null of equal fractional differencing parameter across sub samples can be re-
jected for both factors for the dummy models, pointing to a sizable increase in persistence, from stationary to non-stationary long memory, following the spreading of the first stress wave. Different, for the FFM and CSM models a significant increase in persistence can only be found for the second factor.

Finally, anticipating some of the results obtained through the estimation of the FIFVAR model, both long memory and structural change can be detected also in the volatility of the estimated common long memory factors. The degree of long memory is however not very large, with estimated fractional differencing parameter of about 0.10 and 0.23 for the first and second common long memory factor, respectively.\textsuperscript{13} As is shown in Figure 4, the change in the level and range of variation of the conditional standard deviation process, following the setting in of the crisis, is remarkable. Both similarities and differences can be detected across factors. For instance, for both factors the increase in volatility was particularly strong at the onset of the crisis in August 2007, requiring about one and two months to stabilizing about the new higher levels, for the first and second factor, respectively. Further instability can be detected, around December-February 2008, for the second factor. Finally, an additional increase in volatility can be detected for both factors following Lehman bankruptcy in mid September 2008. For both factors the reversion to pre-Lehman volatility levels is already evident starting from mid December 2008.

Overall the empirical evidence allows to draw some clear-cut conclusions on the copersistence properties of the EE interest rate spreads. First, the long-term evolution of credit/liquidity risk is very similar across maturities, as a single common break process explains over 90% of the variance for each maturity. Hence, when a crisis hits the interbank market, the entire term structure is affected. As already pointed out by the structural break analysis, the break process in the EE spreads can be related to the two waves of bank stress, which have occurred since August 2007. As shown in Figure 3, the common break process component, indeed reflect the timing of the banking crisis. Second, the medium-term evolution of credit/liquidity risk shows both common and idiosyncratic dynamics. In fact, while the first principal component accounts for dynamics which are common to all the EE spreads, and is dominating for maturities beyond 1-month, the second factor mostly explain dynamics common to the shortest end of the term structure. Hence, there seems to be portions of persistent credit/liquidity risk which are shared across all the maturities, but also portions of persistent risk which are

\textsuperscript{13}Adaptive FIGARCH(1,d,1) models, with cubic spline dummy intercept component for the conditional variance equation have been estimated for both (the final) common long memory factors. Estimation is performed directly on the common factor residuals obtained through filtering using median estimated parameters.
shared only by maturities at the very short end. The latter appear to be most persistent. Finally, the crisis has determined an increase (a doubling for the first factor and a threefolds increase for the second factor) in persistence, leading to a transition from a state of stationary long memory \((0 < d < 0.5)\) to a state of non stationary long memory \((0.5 \leq d < 1)\), making common shocks to dissipate more slowly than before.\(^{14}\) The crisis has also determined an abrupt, sizeable (fourfolds) and persistent increase in common factors volatility, which has not shown any evidence of reversion towards pre-crisis levels within the sample investigated.

6 Some issues related to the global dimension of the crisis

The evidence so far discussed is related to the euro area money market. Yet, the persistent features uncovered are not peculiar to the euro area, but due to the global nature of the crisis, likely to be shared by major financial markets. For comparison and robustness assessment, the persistence analysis has been repeated using the whole term structure for the LIBOR-OIS (LO) spreads, i.e. the one-week and two-week maturities and the one-month through the one-year maturities.\(^{15}\)

Overall the findings for the LO spreads are strongly consistent with the results for the EE spreads, along all the dimensions considered by the persistence and copersistence analysis:

- spreads are strongly persistent: the average fractional differencing parameter is about 0.93 (0.041); persistence is accounted for by both long memory and structural breaks;
- structural breaks: the location of the break points is similar to what found for the euro area, i.e. large change in the mean and volatility of the spreads have occurred in correspondence of the setting in of the two stress-waves; while the strongest evidence of breaks is provided by the DM and

\(^{14}\)The \(0.5 \leq d < 1\) case is often referred as the non stationary, yet mean reverting, long memory case. The mean reversion property depends on the fact that the effects of shocks eventually dye out, i.e., provided \(d < 1\), the sequence of impulse response weights converges to zero asymptotically. It is the dissipation of shocks that allows one to denote these non covariance stationary processes as “mean reverting” (Robinson, 2003; p.20). Yet this characterization is not fully accepted in the literature. For instance, Phillips and Xiao (1999, p.34) have argued against the latter interpretation, due to the lack of covariance stationarity.

\(^{15}\)For reasons of space detailed results are not reported, but are available upon request from the authors.
CSDM models, clear-cut evidence is however also provided by the FFM and CS models:

- **cobreaking**: independently of the break model, a single common break process accounts for almost 100\% of total variance for the break process components across maturities (Figure 4); the latter factor accounts for over 90\% of total variance for each spread with maturity beyond two months; for maturities within one month the percentage of explained variance is in the range 65\% to 78\% for the selected DCSM model;

- **long memory**: albeit sensitive to the break model employed, strong evidence of long memory in the break-free series can be found. Average figures from the FFM, CS, DM and DCSM models are 0.613, 0.575, 0.508, and 0.493, respectively. The degree of persistence is not constant along the term structure, being higher for shorter maturities than for longer ones;

- **common long memory factors**: two common long memory factors are sufficient to account for almost 100\% of total variance (Figure 4); the first factor affects all the maturities, with impact weakest at the very short end of the term structure (below 55\% within the 1-month maturity) and strongest at medium- long term maturities (over 80\%); the second factor is on the other hand strictly related to the shortest end of the term structure (about 45\% on average within the 1-month maturity);

- **the crisis has determined a significant increase in the persistence of the two common long memory factors, i.e. about 70\% and 50\% for the first and second factor, respectively (DM and DCSM models). The transition from stationary to non stationary long memory is also detected as a consequence of the crisis, albeit LO spreads appear to be relatively more persistent than EE spreads before the setting in of the crisis, but relatively less persistent over the crisis. Hence, the latter finding suggests that, over a turmoil, shocks may have a more long lasting impact in the EA than in the US. Also the normalization of the interbank market may then occur more quickly in the US than in the EA, as, following the correction in the long-term level, break-free spreads would adjust more rapidly in the US than in the EA.

By comparing the common permanent and persistent components extracted from EA and US data, a close positive association between the common break process components can be noted: independently of the break process estimation method, the correlation coefficient is very close to one for the full sample (0.98 to 0.99), as well as for the pre-crisis (0.85 to 0.92) and crisis samples (0.94 to 0.98). A positive linkage, yet of weaker intensity can also be detected for the the common long memory factors. Concerning the preferred break process estimation method, i.e. the DCSM approach, over the full sample the correlation coefficient is 0.29 and 0.50 for the first and second factor respectively; comovement appears to be stronger over the cri-
sis period than over the precrisis period for the first factor (0.39 and 0.19, respectively), while comovement is of similar intensity for the second factor (0.44 and 0.51, respectively).

Overall, the findings are consistent with the view that the global dimension of the crisis is captured by the permanent/long-term (common break process) component of the risk spreads, while the common long memory factors describe more idiosyncratic national-level adjustment dynamics. Interestingly, according to estimates, while credit risk in the US and the euro area was very close over the pre-crisis period, i.e. the EE-LO spread was about -3.2bp, over the first stress wave (August 9th 2007 to September 15th 2008) a reversal took place, with the EE-LO spread having averaged at about 12bp. Again a reversal took place in the aftermath of the second stress wave, with the EE-LO spread having been negative (-28bp on average) for most of the second stress wave period. The findings have interesting implications, concerning the direction of contagion across the euro area and the US money markets. While the first stress wave started with a bad euro area news - on August 9 2007 the French bank BNP Paribas revealed inability to value structured products for three of its investment funds-, the second stress wave started with a bad US news - on September 15 2008 the US bank Lehman Brothers went to bankruptcy. From the sign of the EE-LO spread, at least in its aftermath, the relative importance of the shock across countries can then be gauged, as well as the direction of international contagion.

7 The FI-F-VAR model

In the light of the results of the persistence and co-persistence analysis, pointing to a single break process and two common long memory factors, the dimension of the FI-F-VAR model is seventeen equations, corresponding to the fifteen money market EE spreads plus the two common long memory factors. On the basis of the detected instability in the persistence parameter, the model has been estimated by allowing the fractional differencing parameter to take different values for the pre-crisis and crisis period, consistent with the findings of the persistence analysis (Table 3).\(^\text{16}\)

\(^{16}\)The values employed are 0.24 and 0.44, for factor 1 and 2, respectively, over the pre-crisis period; on the other hand, figures for the crisis period are 0.89 and 0.87, respectively; for the actual series the values employed are 0.44 and 0.89 for the pre-crisis and crisis period, respectively. The selection of the latter values for the actual series follows from the property of integrated process, according to which the order of integration of a linear combination of non cointegrated factors is determined by the order of integration of the most persistent factor.
Following the thick modelling strategy of Granger and Jeon (2004), median estimates of the parameters and confidence intervals have been computed by selecting the order of the short memory autoregressive polynomial \((C(L))\) by information criteria, yielding a first order model, and then setting to ten the order of the long memory autoregressive polynomial \((\Phi(L))\) and to 1000 the number of Monte Carlo replications.

Interest rate spread series have been ordered from the shortest to the longest maturities; given the orthogonality of the factors and the assumed lack of spillover of idiosyncratic shocks, the latter ordering is immaterial for the computation of the impulse response functions and the forecast error variance decomposition. Consistent with the breaks in the unconditional variance of the EE spreads detected by the persistence analysis, the unconditional variance-covariance matrix employed for the policy analysis has been allowed to change according to the sub period (pre-crisis/crisis) investigated.

### 7.1 Forecast error variance decomposition and impulse response analysis

As shown in Table 5, the findings of the forecast error variance decomposition are clear-cut.

Firstly, independently of the maturity, the contribution of the common factor shocks to fluctuations is similar for both horizons over the pre-crisis period, i.e. 57% to 92% at the 1-day horizon and 48% to 99% at the 20-day horizon; 90% on average for both cases; differently, over the crisis period the common shocks are always dominating at long horizons (85% to 100% at the 20-day horizon; 98% on average), yet dominating at short horizons from the 4-month maturity onwards only (14% to 42% from 1-week to 3-month, 29% on average; 77% to 99% from 4-month to 1-year, 96% on average). Hence, as a consequence of the crisis, short-term fluctuations have become more idiosyncratic, particularly at the very short-end of the term structure (particularly large is the contribution of the own idiosyncratic shock at the 1-week horizon, i.e. about 90%, and still sizable within the three-month maturity, i.e. 70% on average).

Secondly, consistent with the principal components analysis, the two common factors bear a different economic interpretation. The first factor, which affects all the maturities and is, in general, more dominating at long than short horizons and for long end rather than the short end of the term structure, may be interpreted in terms of a level factor. Over the pre-crisis period, the latter never accounts for more than 30% of fluctuations within the 3-month maturity and no less than 40% for longer maturities. Interestingly,
a hump shaped profile can be detected, with the *level* factor being relatively more important for medium-term maturities (3- to 9-month) than at the short or long end of the term structure. A similar evidence can also be found for the crisis period. Yet, for the latter period, the *level* factor yields a more uniform contribution across maturities. For instance, while its contribution, at the 1-day horizon, is never above 20% within the 3-month maturity, at the 20-day horizon its contribution is never below 30%.

The second, *slope factor* is on the other hand dominating at the very short and long end of the term structure, albeit important differences can be detected for the pre-crisis and crisis periods. Over the pre-crisis period, the *slope* factor never accounts for less than 50% of total fluctuations for maturities within the 3-month and beyond the 9-month horizon, for both the 1-day and 20-day horizon. On the other hand, over the crisis period, due to the increased importance of idiosyncratic fluctuations, the proportion of accounted variance is lower, i.e. never larger than 30% at the 1-day horizon (within the 3-month maturity), and just over 50% at the 20-day horizon (yet only within the 1-month maturity); the contribution of the *slope* factor is then sizable again for maturities at the long end of the term structure, i.e. over 25% from the 9-month maturity onwards at the 1-day horizon.

Concerning the impulse response analysis, as shown in Figures 6-7, major differences can be noted between the pre-crisis and crisis periods, both in terms of magnitude and persistence of common factor shocks, as well as of response profiles. Important differences can also be noted, within each period, across maturities; the latter can be easily gauged by comparing the findings for the 1-week and 1-year maturities.

Concerning level shocks, both the persistence and magnitude of the impact increase, in general, with the maturity of the EE spreads. For instance, over the pre-crisis period, the level shock has a fivefold larger impact on the 1-year EE spread than on the 1-week EE spread; moreover, while the rate of decay of the shock is much faster for the 1-week rate, with a zero point impact attained already after one day, for the 1-year rate about twenty days are required for full point dissipation; a similar gap in the magnitude of the impact across maturities can also be detected for the the crisis period; yet, as shown, by the response profiles, shock persistence is much higher over the crisis period (hump-shaped profile) than over the pre-crisis period (monotonic decay), with dissipation occurring well beyond twenty days.

Concerning slope shocks, a similar impact, in absolute terms, can, on the other hand, be found across maturities. Yet, beyond the 3-month maturity, different from shorter maturities, a positive slope factor shock exercises a negative impact on the EE spreads. Moreover, different from the level factor shock, slightly stronger persistence can also be detected for shorter maturities
than for longer maturities for both periods, while, similarly to the level factor shock, the rate of decay of shocks is much faster over the pre-crisis (monotonic decay) than the crisis period (hump-shaped profile).

As shown in Figure 8, differences between periods can also be found concerning the effects of idiosyncratic shocks. While the response profile is similar, pointing to a monotonic decay in both cases, over the crisis period a fivefold larger impact can be detected. Moreover, stronger persistence can be detected for shorter maturities than for longer maturities, requiring about ten and five days, respectively.

8 Conclusions

In this paper we tested for structural breaks in the mean and variance of the EURIBOR-OIS spreads and, in addition, we tested for other forms of persistence, i.e. long memory, using an econometric framework that allows to account for both features. Not surprisingly the main findings are that most of the non-stationarity in the EURIBOR-OIS spreads can be associated with the two waves of magnified stress in the interbank market, the first after 9 August 2007 and the second after 16 September 2008. As the break process describes the long-term evolution of the spreads, the findings point to long lasting (permanent) effects of the financial market crisis on the credit risk, liquidity risk and investor sentiment. Deviations of the EURIBOR-OIS spreads from their long-term (time-varying) values, measured by the break process, tend to be corrected slowly due to their long memory feature. We found that the increasing trend in the EURIBOR-OIS spreads was broken and reversed after the ECB cut its key policy rate by 75 bps, a move that took markets by surprise (i.e. the cut was larger than the markets expected). This, together with other policy measures, may have paved the way for a gradual reversal in market sentiment, and reduction in credit and liquidity risk. These features deserve further research namely by introducing policy measures explicitly into the econometric framework, which is a task left for future work. Overall, our findings are consistent with the global dimension of the crisis given the high correlation found among the break process in the euro and US dollar spreads.
References


Figure 1: Euribor-Eonia interest rate spreads (top plots) and 20-day moving standard deviations (bottom plots), for the 1-week (w1) and 1-year (y1) maturities.
Figure 1: Estimated break processes from dummy model (DM), flexible Fourier model (FFM), cubic spline model (CSM), and dummy-spline model (DCSM); 1-week (1w) and 1-year (1y) interest rate spreads.
Figure 4: US libor-OIS spreads; common break process (cbp) and common long memory factors (clmf) from the dummy-spline model (DCSM).
Figure 5: US libor-OIS spreads; common break process (cbp) and common long memory factors (clmf) from the dummy-spline model (DCSM).
Figure 6: Impulse responses to a unitary level factor (common factor 1) shock for the pre-crisis (left hand side plots) and crisis (right hand side plots) periods: point responses across maturities (from 1-week (1w) to 1-year (1y)) (top plots); point responses with 95% confidence interval (middle and bottom plots).
Figure 7: Impulse responses to a unitary slope factor (common factor 2) shock for the pre-crisis (left hand side plots) and crisis (right hand side plots) periods: point responses across maturities (from 1-week (1w) to 1-year (1y)) (top plots); point responses with 95% confidence interval (middle and bottom plots).
Figure 8: Impulse responses to a unitary idiosyncratic shock for the pre-crisis (left hand side plots) and crisis (right hand side plots) periods: point responses across maturities (from 1-week (1w) to 1-year (1y)) (top plots); point responses with 95% confidence interval (middle and bottom plots).