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Abstract
We analyze the dynamics of the bank interest rates on the new short-term loans granted to non-financial corporations in seven countries of the euro area (France, Germany, Greece, Ireland, Italy, Portugal and Spain). Our specification is based on a multivariate diffusion model, involving factors and stochastic volatilities. In the application, we use a harmonized monthly database collected by the national central banks of the Eurosystem, over the period January 2003-November 2012. We estimate the model within a Bayesian framework, using Markov Chains Monte Carlo methods (MCMC). Unlike the results on spot rates in the empirical financial literature, we find that bank interest rates do not display evidence of mean reversion, and that the variance increases with the level of the bank rates only for a few countries. Moreover, we notice that the correlations between changes in the rates are not constant over the whole time period, and peak during the last months of 2008. Afterwards, they return more or less quickly to their previous level for some countries, while they remain lower for others. From this standpoint, the patterns within the euro area became more heterogeneous after the years 2008-2009.

JEL Classification: E430; G210.
Keywords: bank interest rates; diffusion model; stochastic volatility; Bayesian econometrics.

Résumé
Nous analysons l'évolution des taux d'intérêt des nouveaux prêts bancaires à court terme accordés aux sociétés non financières dans sept pays de la zone euro (France, Allemagne, Grèce, Irlande, Italie, Portugal et Espagne). Notre spécification est fondée sur un modèle de diffusion multivarié, à facteurs communs et sur un modèle de volatilité stochastique. Nous utilisons dans l'application des données mensuelles et harmonisées, collectées par les banques centrales nationales de l'Eurosystème, sur la période allant de janvier 2003 à novembre 2012. Nous estimons le modèle dans un cadre bayésien, avec des méthodes de Monte Carlo par chaînes de Markov (MCMC). Contrairement aux résultats sur les taux spots de la littérature empirique en finance, les taux d'intérêt des crédits bancaires n'affichent pas un retour à la moyenne ; en outre, la variance n'augmente avec le niveau des taux que pour quelques pays. De plus, les corrélations entre les variations des taux ne sont pas constantes sur la période étudiée. Ainsi, un pic est atteint au cours des derniers mois de 2008. Ensuite, ces corrélations reviennent plus ou moins rapidement à leur niveau précédent dans certains pays, alors qu'elles lui restent inférieures dans d'autres. De ce point de vue, les évolutions des taux au sein de la zone euro sont devenues plus hétérogènes après les années 2008-2009.

Classification JEL : E430; G210.
Mots Clés: taux des crédits bancaires, modèle de diffusion, volatilité stochastique, économétrie bayésienne.

1. Introduction

Most central banks provide short-term liquidity to banks at a given rate against some eligible collateral. Banks can then lend to private (non financial firms, households, etc.) or public sector. This is generally referred to as the interest rate channel well established in textbooks. In order words, central banks implement the monetary policy through the interest rates. Variations in the policy rates lead to more or less changes in bank interest rates, because of the competition among banks. Since prices are sticky, this affects the real interest rate and in turn the other aggregates, even in the absence of a change in total lending. An abundant literature is dedicated to the interest rate channel in various countries. Assessments on its importance in the Euro area are reported in several studies (see for instance, Angeloni *et al.* (2003)).

The financial crisis shed a crude light on the major role of banks in supplying loans to the economy. Ivashina and Scharfstein (2010) show a sharp drop in the syndicated loans in the months following the failure of Lehman Brothers (September 2008). They also conclude that banks were heterogeneous in their cut of syndicated lending in the US, depending on their access to funding. Jimenez *et al.* (2010) find a similar result in Spain, for all bank loans granted to non-financial corporations. Campello *et al.* (2010) notice that the number of firms, in the U.S., Europe and Asia, forgoing investment opportunities due to the inability to collect external funds doubled at the end of 2008.

Whereas the evolution and the effects on the macroeconomy of the value of loans provided in the aftermath of the collapse of Lehman Brothers in the Fall of 2008 is empirically well established (see for the Euro area, Giannone *et al.* (2012), Lenza *et al.* (2012)), the evidence on the cost of bank loans is much more limited.

Secondly, firms' funding relies essentially on banks in most euro area countries. Bank interest rates are therefore a major component of the cost of new funds faced by firms, which impacts their balance sheets potentially on the long-run. Thirdly, the sovereign debt crisis in the Euro area raises the concern of the credit markets' heterogeneity among countries. Broadly speaking, banks hold bonds issued by their States and States guarantee their banks. An increase in the cost of one's funding has direct consequences on the other's default risk, potentially leading to a fragmentation of the credit market. Fourthly, the results simply help in improving our understanding of the driving factors of bank interest rates.

In this paper, we specify a multivariate diffusion model. Indeed, bank rates commoves remarkably well across countries in the euro area. While cross-country comparisons can be based on estimations of the same model repeated using data from different credit markets, ignoring their interdependence can yield a partial assessment of their dynamic. Dependence among series is introduced through latent common factors. They traduce common drivers to the euro area countries, for instance the monetary policy or external shocks impacting all countries. Factors are allowed to be time-varying for two reasons. First, the common drivers do not need to be constant over time. Second, the implied correlations among changes in the bank interest rates can vary over time. This flexibility is especially important in time of the sovereign debt crisis, when there is no reason to suppose the association between the interest rates remains unchanged. We consider common factors as unobserved. This is clearly a shortcut, as one could be interested in the explicit dependence of the bank interest rates on predictors such as the monetary policy rates, or rates on the interbank markets, among others. Indeed, many models of bank behavior derived from the industrial organization literature (e.g. Cournot models, Monti Klein models) predict that in a stable environment, bank rates commove with the cost of liquidity. Those predictors are however highly correlated, raising multicolinearity issues, and their respective influences can vary over a time period characterized by so many shocks. Therefore, we do not investigate such dependence or the underlying causality here. Our specification helps in indentifying common phenomenon with economic consequences while remaining parsimonious and agnostic, in the sense that we do not rely on an economic model.

As discussed above, the model is designed to characterize parsimoniously the banks short-rates joint dynamic across countries in times of potentially huge shocks. We estimate models using data collected in France, Germany, Greece, Ireland, Italy, Portugal and Spain. Data come from the Monetary Interest Rate survey database, which are harmonized at the level of the Euro area. To help further in performing relevant comparisons, we consider the identical period span from January 2003 to November 2012 for all countries. It includes the sub-period corresponding with the aftermath of the collapse of Lehman Brothers in the fall of 2008, which could be seen like times of huge volatility, and ensuing recourse to unconventional monetary policies, where the influence of the monetary policy rate can be expected to be weakened. We estimate the model following a Bayesian approach, using Markov chain Monte Carlo (MCMC) methods. More specifically, sampling is based on a Hamiltonian Monte Carlo (HMC) method proposed by Hoffman and Gelman (2013), namely the No-U-Turn Sampler.

Our paper is also connected to the applied literature on the cost of bank loans. Following the influential papers by Bernanke and Blinder (1992) and Bernanke and Gertler (1995), numerous macro-level studies investigate the pass-through from the monetary market to the credit market. Using data at the individual loan-level, Berger and Udell (1992) show that bank rates are stickier than Treasury bill rates. Hannan and Berger (1991) conclude that rigidity of bank rates depends on the competition among banks. Many studies conclude that the pass-through depends on the characteristics of the banks, leading to the analysis of the so-called bank lending channel (Kashyap and Stein (2000), Kishan and Opiela (2000), Altunbas *et al.* (2002), Gambacorta (2008)).

The paper proceeds as follows. The data we use are presented in Section 2. Section 3 presents a brief survey of the literature on short rate models. We develop in Section 4 a multivariate diffusion model with stochastic volatilities. We discuss the choice of the prior and the Bayesian inference in Section 5. Empirical results are reported in Section 6, and Section 7 concludes.

2. Bank short-rates data

The analysis of monetary transmission *via* the credit channel asks for a reliable measure of the interest rates applied by Monetary and Financial Institutions (MFIs). In order to compare these interest rates in the Euro zone, the European Central Bank decided in December 2001 to harmonize the existing surveys ran previously by the National Central Banks. This leads to the MFI Interest Rates (MIR) survey, where the types of rates, financial instruments, reporting populations and methods of calculation are harmonized.[1] The resulting data are aggregated over contracts at the national level.

The interest rates are expressed as annual percentage rates at the aggregate levels, which are derived from the individual new contracts agreed between a MFI and a non-financial corporation (NFC).[2] New agreements are all financial contracts that specify for the first time the interest rate of the loan, and all new negotiations of existing loans. New businesses therefore do not include automatic prolongations of existing contracts that do not involve any re-negotiations of the terms and conditions. Revolving loans and overdrafts, as well as convenience and extended credit card debt, are also excluded from the underlying sample. The agreed rates can be lower than the advertised rates, because the customer is able to negotiate a better rate. The MFI interest rates statistics on new business therefore reflect the agreed conditions on the loan markets at the time of the contract. Therefore, it reflects the demand and supply, including variations in the cost of funds faced by banks, competition among banks, types of financial institutions or products.

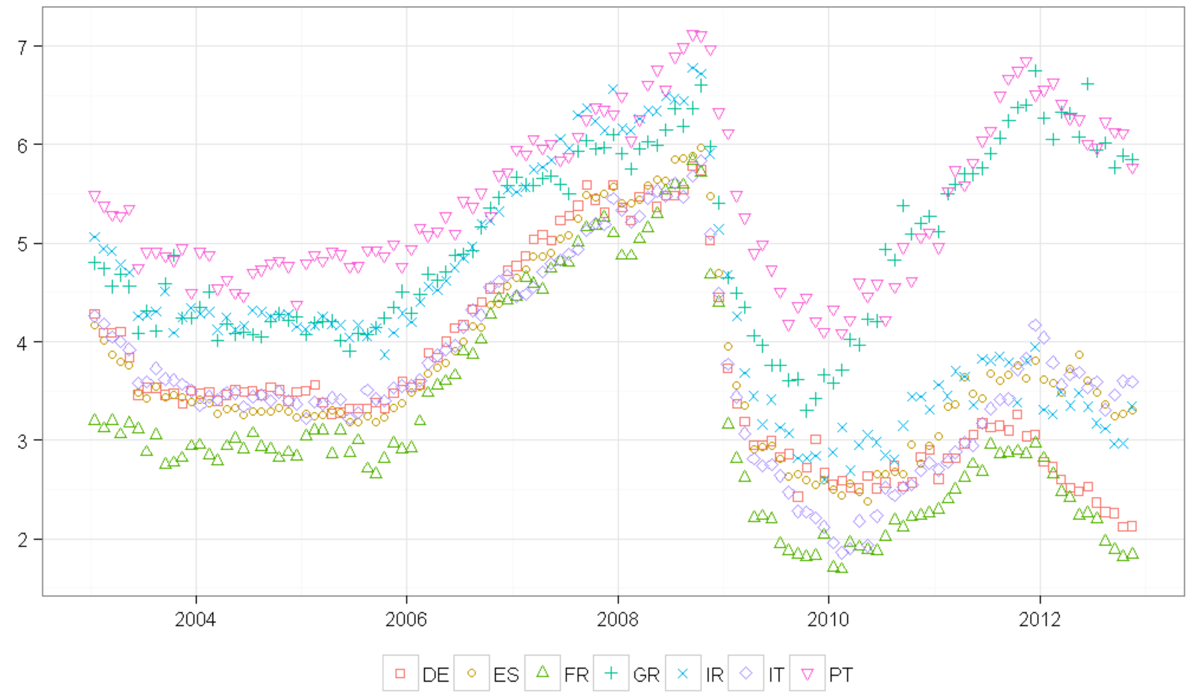
[1] The details of this harmonization are described in European Regulation ECB (2001).

[2] NFCs are all firms excluding insurance companies, banks and other financial institutions.

Our dataset has been drawn from the MIR survey. It consists of monthly observations on new loans with maturity up to one year to non-financial corporations from January 2003 to November 2012. We use data on the loans granted in France, Germany, Greece, Ireland, Italy, Portugal and Spain.

Figure 1 displays the evolution of the bank interest rates in these seven European countries. Despite differences in their levels, the interest rates appear to comove remarkably up to 2010. While they remained rather stable or even slightly decreasing between 2003 and the end of 2005, they began to rise in 2006 until the third quarter of 2008. Following the failure of Lehman Brothers, they decreased at the end of 2009 on average in these seven countries of about 325 basis points. The short-rates have been split in three groups since the beginning of 2010: in the first group (Germany and France), they vary slightly and remain lower than their average over the sub-period 2003-2006; in the second one (Greece and Portugal), they also grow up again since 2010 and reach levels close to the ones observed just before September 2008; at the end of the period, the last group is made of Italy, Ireland and Spain whose interest rates are in an intermediate situation.

Figure 1: Monetary and financial institutions interest rates to non-financial corporations, January 2003 - November 2012.



The interest rates series are non-stationary but are integrated of order 1 (*I(1)*). As a consequence, we focus in the following on their variations from one month to the other (Table 1). The variations in interest rates are plotted in Figure A.1, in Appendix A. Many remarks can be made. First, as mentioned above, the increase in the short-rates from 2006 to 2008 is gradual and made of small variations. This translates into slightly positive values of the difference in the interest rates between 2006 and 2008. Note that these values are always less than 50 basis points and generally close to zero. Second, we observe a sharp decline in the rates over the period September 2008 - October 2009, yielding huge negative variations in the series in difference for all countries. Third, changes in the interest rates in Spain and Greece are more important after 2010 than before September 2008.

Table 1 contains descriptive statistics on changes in the short-rates. The averaged first differences of the interest rates range from -2 basis points (Germany) to 1bp (Greece), and the standard deviations lie between 17 bp (Spain) and 25 bp(Greece). As the medians are positives, except for Ireland, it is likely the means reflect the huge negative variations occurring between September 2008 and October 2009.

This is reinforced by the negativity of the skewness statistic for all countries, indicating that the left tail of the probability density function is longer than the right one, and that the interest rates mostly lie to the right of the mean. The strongest drop in the interest rates was of -124 basis points and occurred in France from December 2008 to January 2009. The kurtosis for France is the highest and about 12, indicating a sharper peak and fatter tails than in the other countries. Jarque-Bera normality tests suggest that the empirical distributions are not normal, except for Portugal for which we can accept the normality hypothesis at 30% level.

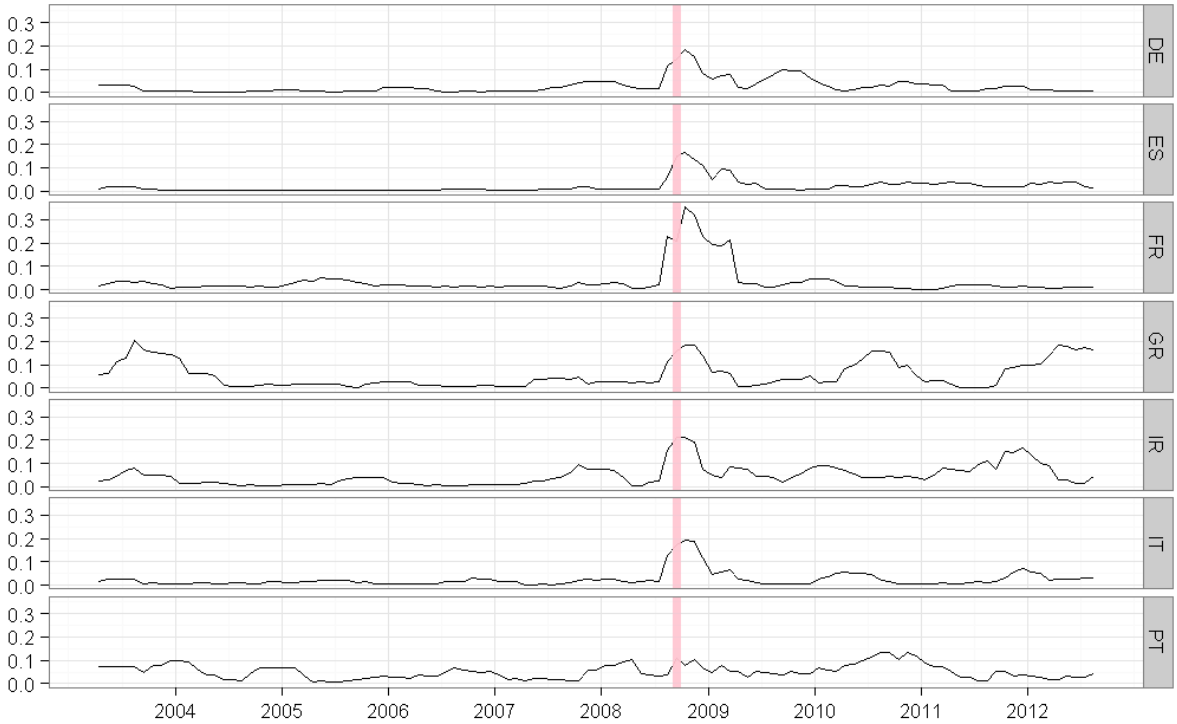
Table 1: Summary statistics and p-values on changes in MFIs interest rates to NFCs

	DE	ES	FR	GR	IR	IT	PT
Mean	-0.02	-0.01	-0.01	0.01	-0.01	-0.01	0.00
Median	0.01	0.02	0.01	0.02	-0.01	0.02	0.02
Sd	0.18	0.17	0.21	0.24	0.23	0.18	0.23
Min	-0.72	-0.78	-1.24	-0.76	-0.81	-0.75	-0.64
Max	0.32	0.30	0.29	0.73	0.47	0.34	0.57
Skewness	-1.25	-1.68	-2.62	-0.53	-0.81	-1.30	-0.33
Excess kurtosis	2.91	5.64	12.08	1.45	1.27	3.46	0.11
Jarque-Bera	0.00	0.00	0.00	0.00	0.00	0.00	0.31
Phillips-Perron	0.01	0.01	0.01	0.01	0.01	0.01	0.01
ADF	0.01	0.04	0.02	0.01	0.04	0.03	0.04
Ljung-Box	0.00	0.00	0.00	0.18	0.02	0.00	0.02
Diebold	0.03	0.00	0.02	0.34	0.13	0.02	0.03
ARCH	0.00	0.00	0.00	0.01	0.00	0.00	0.48

Note: The null hypothesis of the Phillips-Perron and ADF tests is that the series has a unit root. Ljung-Box, Diebold and ARCH p-values are computed using 3 lags.

The rolling variances displayed on Figure 2 show that the estimated variances peak at the end of 2008 and the beginning of 2009 for all countries. As regards Greece, Ireland, Portugal, and to a lesser extent Germany and Italy, this is followed by other similar peaks distributed from the end of 2009 (DE) to 2011 (PT). In addition, ARCH tests enable us to reject the hypothesis of homoskedasticity for all countries but Portugal. These conclusions are in favor of the hypothesis of conditional heteroskedasticity in most countries. Besides, Ljung-Box tests and Diebold's (1986) tests corrected for ARCH effect suggest autocorrelated errors in all countries but Greece.

Figure 2: Rolling variances of the changes in the monetary and financial institutions interest rates to non-financial corporations, January 2003 - November 2012



Note : Rolling variances are computed using one-year time intervals.

3. Short-rate models

The literature on short-rate dynamics points at some of their feature. Previous papers, such as Chan *et al.* (1992) or Andersen and Lund (1997), conclude that short rates are mean-reverting and that their volatilities tend to increase with the level of the interest rate. Their variations are susceptible to scale effects, and one cannot reject the hypothesis they are heteroskedastic. Those features are incorporated in basic diffusion models, which have been extended over time to yield more flexible volatility dynamics.

Univariate diffusion models are often used to capture the stochastic behavior of short-term rates. Many short-term rate models are nested in the following stochastic differential equation:

$$dr_t = (\beta_0 + \beta_1 r_t)dt + \sigma r_t^{\gamma} dB_t, \tag{1}$$

where r_t is the interest rate at time *t*, and dB_t is a Brownian motion. The term $\beta_1 r_t$ allows for some mean reversion. For $\beta_0 > 0$ and $\beta_1 < 0$, the model predicts positive changes in the interest rates when r_t is below the long-run mean $-\beta_0/\beta_1$, and negative changes in the interest rates when r_t is above it. The speed of the mean reversion depends on β_1.

The model allows for dr_t to be more volatile when the interest rates are high than when they are low. Volatility increases as the interest rate increases, at least for scale reasons, and it varies due to changes in the level of the interest rates only. Parameter γ indicates the sensitivity of the variance of the changes in the interest rates to their levels, and is often referred to as the level effect. Equation (1) nests many sub-models. For instance, when $\gamma = 0.5$, Equation (1) becomes Cox *et al.* (1980) model ; when $\gamma = 0$, it is equivalent to Vasicek (1977) model. The interest rate process is explosive if $\gamma \geq 1$. Since the conditional mean and variance of dr_t only depend on r_t, the related short-term rate models are often denominated as one-factor models (see Brigo and Mercurio, (2006), for a review). Hull and White (1987) provide an extension where σ does vary over time.

Chan *et al.* (1992) study Equation (1) in order to empirically discriminate the different short-rate models. Their specification is a discrete-time model derived from the Euler approximation:

$$\Delta r_t = \beta_0 + \beta_r r_{t-1} + \sigma r_{t-1}^{\gamma} \epsilon_t, \tag{2}$$

where ϵ_t is standard gaussian. It has been extended in several directions in practice, especially to allow for a more flexible volatility. Extensions to GARCH volatility include, among others, Longstaff and Schwartz (1992), Koedijk *et al.* (1997), Bali and Wu (2006). Regime-switching GARCH volatilities are studied in Brenner *et al.* (1996) and Gray (1996). An extension to stochastic volatilities is provided by Andersen and Lund (1997). Markov-switching stochastic volatilities are investigated by Smith (2002), Kalimipali and Susmel (2004) and Sun (2005). To our knowledge, the most flexible specification in this vein is described in Chib *et al.* (2002). They investigate, among other, a model with covariates and Student-*t* errors in the mean equation, and covariates in the random variance equation.

For a given γ, ordinary least squares estimator provides consistent but inefficient estimates of the parameters in Equation (4). The coefficients of mean reversion factor do not significantly differ from zero. The explanatory power of the regressions are also poor.

4. A multivariate diffusion model with a factor structure

Our model is a generalization of the univariate diffusion model described above. The previous analysis in Section 2 indicates that MFIs short-rates commoves remarkably well. The analysis of longitudinal variations suggests the presence of common causes driving the short-rates dynamic in the different countries. The underlying drivers are however unknown against the background of a standard diffusion model. We therefore focus on a multivariate model, where the dependence across the series is generated by latent factors.

Let us denote by q the number of countries studied. For the sake of simplicity, we denote hereafter the q vector of the interest rates by r_t. Consider a q-variate time series $\Delta r_t = (\Delta r_t^{\mathrm{DE}}, \dots, \Delta r_t^{\mathrm{PT}})$, t = 1,2,…, T. Variations in bank short-rates are explained by:

$$\Delta r_t = \beta_0 + \beta_r r_{t-1} + B f_t + \Psi_t \epsilon_t,$$

where B is a $q \times k$ matrix, k denotes the number of factors ($k<q$), $f_t$denotes independent realizations from a $k \times 1$ latent process, and ϵ_t denotes a q-vector of series specific gaussian white noises.

Matrix B is the loading matrix. To ensure the identification of the factor model, we use the so-called "hierarchical" constraints, where $b_{ij} = 0$ for $i < j$ and $i \leq k$, and $b_{ii} = 1$ for $i \leq k$. The implications of these constraints are discussed in Aguilar and West (2000). We assume the factors are independent from the error term and across time. They are distributed as $f_t \sim \mathcal{N}(0, G_t)$, where G_t is a diagonal matrix. We write each of its diagonal elements as $\exp\left(g_{t,i}\right), i = 1, \dots, k$. The vector $g_t = \left(g_{t,1}, \dots, g_{t,k}\right)$ is supposed to follow a vector autoregressive process of order 1:

$$g_t = \delta_0 + \delta_1 (g_{t-1} - \delta_0) + \omega_t.$$

The stationarity assumption implies that $|\delta_1| < 1$. The innovations are independent across time but not across series:

$$\omega_t \sim \mathcal{N}(0, W).$$

Non-zero off-diagonal entries in W imply dependence among the (log-) variances of the factors. The factors are therefore the outcome of a multivariate stochastic volatility model.

The idiosyncratic errors have a variance of $\Psi_t \Psi_t'$, where Ψ_t is defined as:

$$\Psi_t = \mathrm{diag}(\exp\left(h_{t,1}/2\right) r_{t-1,1}^{\gamma_1}, \dots, \exp\left(h_{t,q}/2\right) r_{t-1,q}^{\gamma_q}).$$

The residuals are heteroskedastic because of r_{t-1}^{γ} and because we assume h_t evolves randomly over time:

$$h_t = \alpha_0 + \alpha_1 (h_{t-1} - \alpha_0) + \sigma_\eta \, \eta_t,$$

with η_t a $q \times 1$ vector of independent gaussian innovations. We assume its elements η_{tj} $(j = 1, \dots, q)$ are mutually independents. Therefore, the shocks on the idiosyncratic (log-) variances are independent across time and across series. For a given r_{t-1}, the errors evolve according to univariate stochastic volatility models. To ensure stationarity, we impose the restriction $|\alpha_1| < 1$.[3]

[3] See Davis and Mikosch (2009) for a discussion of the strict stationnarity in stochastic volatility models. Kalaylıoğlu and Ghosh (2009) propose a Bayesian procedure to test the assumption of a unit root in Stochastic Volatility (SV) models.

The model above implies time varying correlations for the series in Δr_t. Indeed, since the factors and the errors are independent, conditional on r_{t-1}, g_t, h_t and the parameters, the variance is : $\text{var}(\Delta r_t | r_{t-1}, g_t, h_t,) = BG_tB' + V_t$. For a model with a single factor, the first term in the variance differ from one country to the other at time *t* only due to differences in their loadings. The off-diagonal elements of the variance matrix are explained by the factors and their loadings, whereas the idiosyncratic evolutions are explained by the vector of country-specific terms. In other words, the idiosyncratic component might capture unusual changes in the interest rates specific to a series. The loadings also impact the association between Δr_t and f_t. Indeed, conditional on g_t, $\text{cov}(\Delta r_t, f_t) = BG_t$. For a given factor variance, higher loadings indicate a higher covariance between the change in the interest rate and the factors.

Our specification is similar to the one in Aguilar and West (2000). It is in line with Kim *et al.* (1998), Pitt and Shephard (1999) and Jacquier *et al.* (1999), whose models are extended to time varying idiosyncratic variances and factors with stochastic volatilities. Aguilar and West (2000), and henceforth the specification we use, is the starting point of several extensions aiming either at including wider shocks in the mean equation, or at more flexibility in the factor evolution. On the one hand, a more general framework than the one we study here is proposed in Chib *et al.* (2006), involving jumps in the mean equation and, because the residuals follow a Student distribution, fatter tails. On the other hand, Han (2006) allows for autoregressive factors at order 1. Lopes and Carvalho (2007) include time-varying loadings and Markov switching regimes in their model.

5. Bayesian inference and computation

5.1. Inference in diffusion models and stochastic volatility models

The diffusion model above involves in the variance a nonlinear level effect. Therefore, it cannot be estimated with the standard tools for linear models, unless one is willing to consider γ as fixed. Chan *et al.* (1992) use the Method of Moments to estimate it.[4]

Different procedures have been used for the inference in stochastic volatility models. In most papers, the mean equation is restricted to an error term, so that the factors and parameters of interest come from the log-variance equation. The volatility is latent, and the likelihood contribution of each Δr_t involves an unobservable variance. The full likelihood is thus a *T*-fold integral, which is not amenable to a closed form solution in most cases. Direct optimization of the likelihood is therefore not easily tractable, and the estimations procedures developed in the literature are nonstandard.

Previous papers involving stochastic volatility models estimate them with the method of moments (Scott (1988), Melino and Turnbull, (1990)).[5] However, these procedures have poor finite sample properties (Jacquier *et al.* (1994)). Harvey *et al.* (1994) suggest a quasi-maximum likelihood (QML) procedure. Taking the log of the squared Equation (2) allow them to linearize it, and thus to express the model in a state-space form. The log of the squared residual of Equation (2) is hence expressed as a linear measurement equation. The state error is log-chi-squared. To avoid handling it explicitly, they assume gaussianity and achieve a tractable quasi-likelihood. Harvey *et al.* (1994) provide an algorithm based on the Kalman filter for joint QML estimation of the parameters and volatilities. Broto and Ruiz (2004) survey studies on the properties of the QML estimator in the context of stochastic volatility

[4] Maximum likelihood inference derived from Equation (2), the discrete time approximation is also feasible. Phillips and Yu (2009) survey maximum likelihood estimation of continuous time diffusion models.

[5] The efficient method of moments, also referred to as indirect inference, proposed in Gouriéroux *et al.* (1993) and Gallant and Tauchen (1996), has been used more recently to estimate stochastic volatility models. See Renault (2009) for a survey.

models. As the QML procedure does not rely on the exact likelihood, it is less efficient than the Bayesian approach.

Stochastic volatility models are difficult to estimate because of the presence of unobserved volatilities in the likelihood. Shephard (1993) uses a data augmentation procedure consisting of simulating the log-volatilities, by proceeding with the inference as if the simulated values were actually observed, and by finally iterating between the two steps. He implements a Simulated Expectation Maximization algorithm where the computation of the expectations involves Metropolis-Hastings and Gibbs sampling procedures. The whole procedure can be viewed as a two-step version of the more general Gibbs sampler. Jacquier *et al.* (1994) introduce this method in the Bayesian framework. They provide a MCMC procedure, referred to as a single move procedure, where the latent log-volatilities are sampled one at a time. Remind that MCMC algorithms do not generate independent draws, but autocorrelated ones. Since the log-volatilities follow an autoregressive process, the draws can be highly autocorrelated. The naïve variance estimates would underestimate the true value in such a case, as in regression models where dependence among observations is ignored. This can be accommodated by thinning the chain (see for example Lynch, (2007)). Highly autocorrelated draws are nonetheless often considered as evidence of slow mixing, indicating that the Markov chains require many iterations before one can confidently use the simulations for the inference. So as to reduce autocorrelation in the draws and speed-up convergence of the Markov chains, Kim *et al.* (1998) introduces a procedure to sample jointly the log-volatilities, referred to as a multi-move MCMC algorithm.[6]

5.2. Bayesian inference and computation

In a Bayesian approach, prior beliefs on the set of parameters complete the specification. We build here on previous studies in the Bayesian SV literature. The priors are summarized in Table A.2 in Appendix.

From a subjective point of view, parameters are subject to beliefs formulated in terms of probability distribution called priors. Our full prior can be written as $p(\beta)p(B)p(\delta)p(W)p(\alpha)p(\sigma_\eta)p(\gamma)$, where $\beta = (\beta_0, \beta_r)$, $\delta = (\delta_0, \delta_1)$ and $\alpha = (\alpha_0, \alpha_1)$. The priors on the components of β and B are independent Gaussian, in line with the literature on linear models. We adopt a conservative stand and center these priors on zero, with a standard deviation of 100. Clearly, the range of values encompassed by our prior is far wider than the results reported in the literature on short-rate.

We use independent uniform priors for the elements of δ and α. The empirical counterpart of the long-term variance, namely the variances computed over the whole period, are always lower than 0.06 for each country. The long-term variance, whether the factor one or the idiosyncratic one, is therefore not expected to be greater than 1. The priors on the long-term variances δ_0 and $\alpha_0$hence range over (-20, 0). The priors on δ_1 and α_1 range over]-1, 1[, as mentioned above, to ensure the stationarity of stochastic volatility process.

Parameter W is the variance matrix of the innovations on the factor (log-) variances. Since shocks inducing booms and busts at the international level are likely to be correlated, we do not restrict W to be diagonal. We follow Aguilar and West (2000) and set as prior an inverse Wishart distribution. The prior is centered on diagonal matrix with k + 2 degree of freedom, so that it spreads loosely around a variance matrix obtained under independent factors. It is quite legitimate and common to let prior beliefs adjust to preliminary inspection of the data, and the diagonal elements of the prior mean are set in accordance to preliminary estimates.

6 Kim *et al.* (1998) also use particle filtering to approximate the log-volatilities given the data. Particle filter allows, when a new observations is available, to compute the corresponding volatility without running again the MCMC sampler. Recent developments on particle filters applied to SV models include Jacquier *et al.* (2010) Carvalho *et al.* (2010).

The prior on σ_η^2 is an inverse gamma distribution, as in Kim *et al.* (1998), with both parameters set so that the prior mean of σ_η is 1 and its' variance is of 1000. This prior is thus fairly uninformative, and allows for very large shocks on the volatility.

We assume a uniform prior for γ ranging from 0 to 2, in line with Chib *et al.* (2002). This prior covers the estimated values reported in the literature on short rate models. The prior excludes negative γ, as it is assumed in these models to be positive to ensure a finite variance. Assigning a zero prior probability to negative values leads to a zero posterior probability. Therefore, this prior enforces the positivity restriction from the diffusion model directly in the inference.

We need to compute the posterior distribution implied by the prior and the likelihood to derive the Bayesian estimator. It does not have a closed form here, but we can however approximate it using Markov Chains Monte Carlo (MCMC) procedures. The quantities of interest are approximated with Monte Carlo methods applied to draws from Markov chains with elements following the posterior distribution. Shephard and Kim (1994) show in univariate models that an issue might arise when the volatility is highly autocorrelated and its disturbances very concentrated. In this case, the sampled (log-) volatilities can be very highly autocorrelated over numerous draws, leading to very little movement in the chains. This slows down convergence, and yields algorithm with poor numerical performances. To reduce the autocorrelation among draws, Kim *et al.* (1998) propose a multimove MCMC sampler that has a huge impact on the ensuing literature. We use here instead Hoffman and Gelman (2013) No-U-Turn Sampler, a Hamiltonian Monte Carlo (HMC) method. HMC procedures converge more quickly than simpler methods, such as random walk Metropolis or Gibbs sampling, for many models. However, it asks for some fine tuning of two user-specified parameters. Hoffman and Gelman (2013) provide an automatic procedure to set these parameters, allowing easy tuning of the algorithm and replicability of the Markov Chains.

We run four chains, starting with over dispersed initial values, of 30 000 iterations. Results turn out to not be sensible to the choice of the initial values. Convergence is assessed using both Gelman and Rubin (1992) statistics and Heidelberger and Welch (1983) tests. All chains reached an equilibrium within 10 000 iterations. All the results reported below are based on post-convergence iterations.

6. Empirical results

This section presents the Bayesian estimates of the factor model. The model allows so far for several factors. We reduce it to a unique factor and report below the corresponding estimates. In a last subsection, we examine the robustness of the results to an alternative mean equation, taking explicitly into account the peculiarity of the few months following September 2008.

6.1. Factor model

The factor loadings are identified due to restrictions on the design on B described in Section 4. When there is a single factor, they imply that the factor loading of the first series is normalized to 1. Therefore, the identification issue impacts the order of the series in Δr_t. Indeed, when $(\beta_0, \beta_r) = 0$, the first series is equal to the factor plus a residual. The first series acts as a benchmark, and we set it as the evolution of bank interest rates in Germany. The factor loadings therefore measure departure in the other countries from the latent common factor, identified taking as a benchmark the credit rates in Germany.

Bayesian estimates of the multivariate diffusion model are reported in Table 3. These results indicate no significant mean reversion.[7] Some posterior distributions of γ do have all their mass clearly apart

[7] Alternative models, where β_0 or β_1 are specified as factors, have been estimated. They provide similar results in the sense that the elements of these vectors are never significant.

from zero. γ is the only parameter from the diffusion model that turns out to be significant for a few countries, with the highest magnitude estimated, by descending order, in Spain and France. As indicated in Table 1, the distributions of changes in the interest rates are the most skewed for those countries, with left tails longer than in the others. One can thus think that the estimated level effect depends on the observations where the rates fell abruptly from their maxima, typically in the months following September 2008.

Table 3: Estimated coefficients of the multivariate diffusion model

	β_0			β_r			$\exp(\delta_0/2)$			δ_1			σ_ω		
	Mean	Lower	Upper	Mean	Lower	Upper	Mean	Lower	Upper	Mean	Lower	Upper	Mean	Lower	Upper
All	0.01	-0.03	0.06	0.00	-0.01	0.01	**0.09**	**0.05**	**0.18**	**0.87**	**0.68**	**0.99**	**0.67**	**0.40**	**1.08**
	B			γ			$\exp(\alpha_0/2)$			α_1			σ_η		
	Mean	Lower	Upper	Mean	Lower	Upper	Mean	Lower	Upper	Mean	Lower	Upper	Mean	Lower	Upper
DE	1.00	-	-	0.37	0.00	1.38	**0.06**	**0.02**	**0.12**	**0.82**	**0.29**	**0.99**	**0.44**	**0.15**	**0.87**
ES	**1.10**	**0.88**	**1.34**	**0.84**	**0.05**	**1.99**	0.02	0.00	0.14	**0.95**	**0.83**	**1.00**	**0.43**	**0.15**	**0.93**
FR	**1.17**	**0.87**	**1.60**	**0.61**	**0.12**	**1.23**	**0.06**	**0.03**	**0.11**	0.33	-0.71	0.93	**0.35**	**0.07**	**0.84**
GR	**1.03**	**0.81**	**1.30**	**0.51**	**0.03**	**1.54**	**0.07**	**0.01**	**0.19**	**0.81**	**0.47**	**0.98**	**0.59**	**0.27**	**1.05**
IR	**1.16**	**0.85**	**1.49**	0.35	0.00	1.05	**0.09**	**0.02**	**0.24**	**0.91**	**0.67**	**1.00**	**0.41**	**0.15**	**0.81**
IT	**1.13**	**0.92**	**1.41**	0.29	0.00	0.97	**0.06**	**0.02**	**0.11**	0.75	-0.07	0.99	**0.45**	**0.10**	**0.96**
PT	**0.72**	**0.39**	**1.09**	0.25	0.00	0.80	**0.14**	**0.05**	**0.22**	0.31	-0.70	0.96	**0.19**	**0.04**	**0.56**

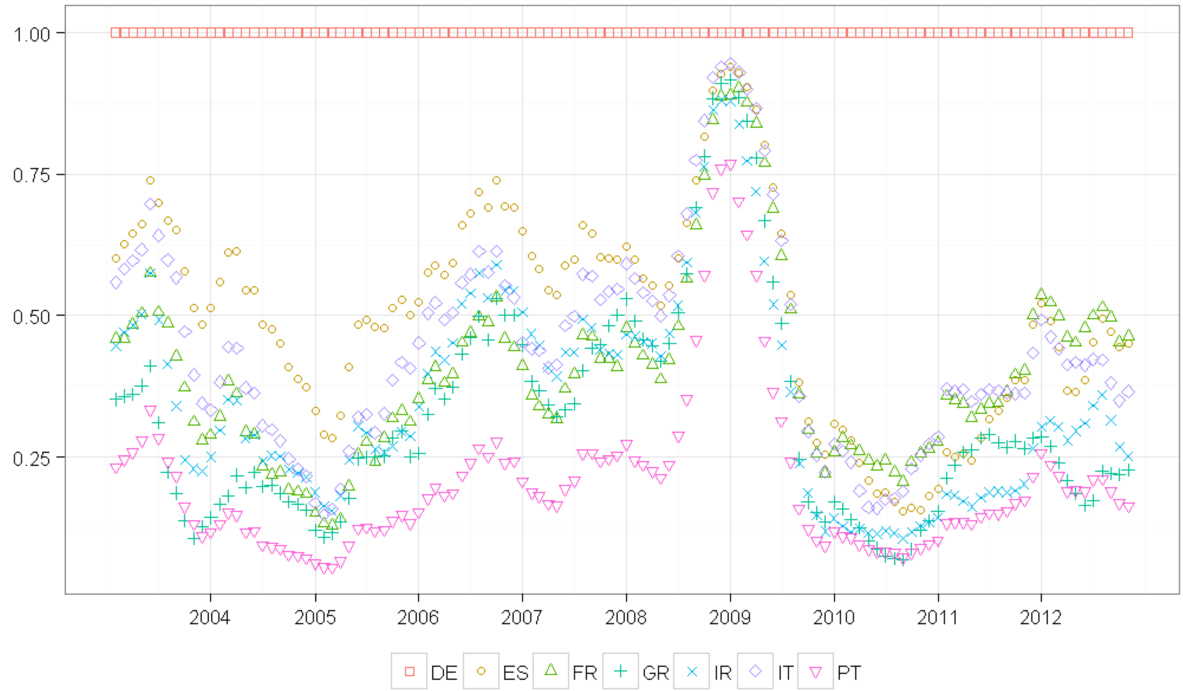
Note: “Lower” and “Upper” denote the lower and upper bounds of the highest posterior density intervals at the 5% level. Estimates in bold types significantly differ from zero at the 5% level.

We report in Table 3 the long-term idiosyncratic standard deviations of the errors in the absence of a leverage effect, measured by $\exp(\alpha_0/2)$. Relatively high long-term standard deviations are estimated, in descending order, for Portugal and Ireland. The estimated autoregressive parameters of the idiosyncratic variances show high and significant persistence in Germany, Greece, Ireland and Spain. Their point estimates range from 0.82 to 0.95, values similar to the ones reported in the literature on short-rates. As regards the other countries (France, Italy and Portugal), we cannot reject the hypothesis that the idiosyncratic variance follow a random walk. To sum up, the contemporaneous idiosyncratic variances tend to remain close to their mean and revert slowly to it after a shock in Germany, Greece, Ireland and Spain, whereas they can depart suddenly from it in France, Italy and Portugal. This is especially true for Italy, the country in the random walk-type group where σ_η is the highest. Besides, the estimates of σ_η are always positive significant, providing evidence of stochastic volatilities.

Table 3 reports the estimated factor loadings. To ensure their identification, the factor loading corresponding to Germany is normalized to unity. They are positive for all countries, indicating that the common driver induces a positive association of the interest rates across countries. The long-run standard deviation of the factor is about 0.09, which is about the same order of magnitude than the idiosyncratic variances without level effect in the variance. The factor (log-) variance is also strongly autocorrelated.

The estimated correlations of the changes in bank rates in any country and Germany are displayed on Figure 3. The correlations are all positives over the whole period. Furthermore, they all vary over time but commove remarkably well. Before mid-2008, the estimated correlations range across countries over an interval whose width is about 0.5. All the correlations peak at the very end of 2008, during the financial turmoils, and reach their maxima close to one. This finding is in line with the abundant evidence in the financial literature, showing that the relationship between the financial markets is reinforced during the booms or burst. Afterward, they drop sharply until mid 2010, and increase smoothly again. Since 2009, the cross-country correlations are lower and more concentrated. They are spread across countries over an interval of width 0.3. These two features indicate less synchronous shocks on the credit markets, and thus insulation of the national credit markets since 2010.

Figure 3: Posterior mean of the correlations with respect to the changes in the bank rates in Germany implied by the factor model, January 2003 - November 2012



7. Conclusion

We show how diffusion models can be applied to analyze the bank loans short-term interest rates dynamics for some euro area countries. The basic model is extended to allow for stochastic volatilities. We examine their performances in the analysis of the short-rates dynamics in the aftermath of Lehman Brothers collapse.

Our results reject the view that bank interest rates dynamics can be analyzed in the same way as short-term riskless rates. Using monthly data, we do not find clear evidence of mean reversion. The level effect in the variance is the only component of a diffusion model that turns out to be significant for a few countries. This stands in sharp contrast with the literature on short-term riskless rates, where the elasticity of a change in the rate with respect to a shock is between 1 and 1.5 (see Chan *et al.* (1992) and Smith (2002) among others), depending on the modeling of atypical time periods. While MFIs' short-rates experienced a sharp fall from high levels at the end of 2008, it does not have to be related to a feature of their intrinsic dynamic.

Our estimates show a weakening synchronization of the changes in the bank interest rates across countries in the euro area after the financial turmoil of 2008-2009. An assessment of the increased heterogeneity of the credit markets at the country level, and their resulting potential fragmentation, could therefore be a topic for further research.

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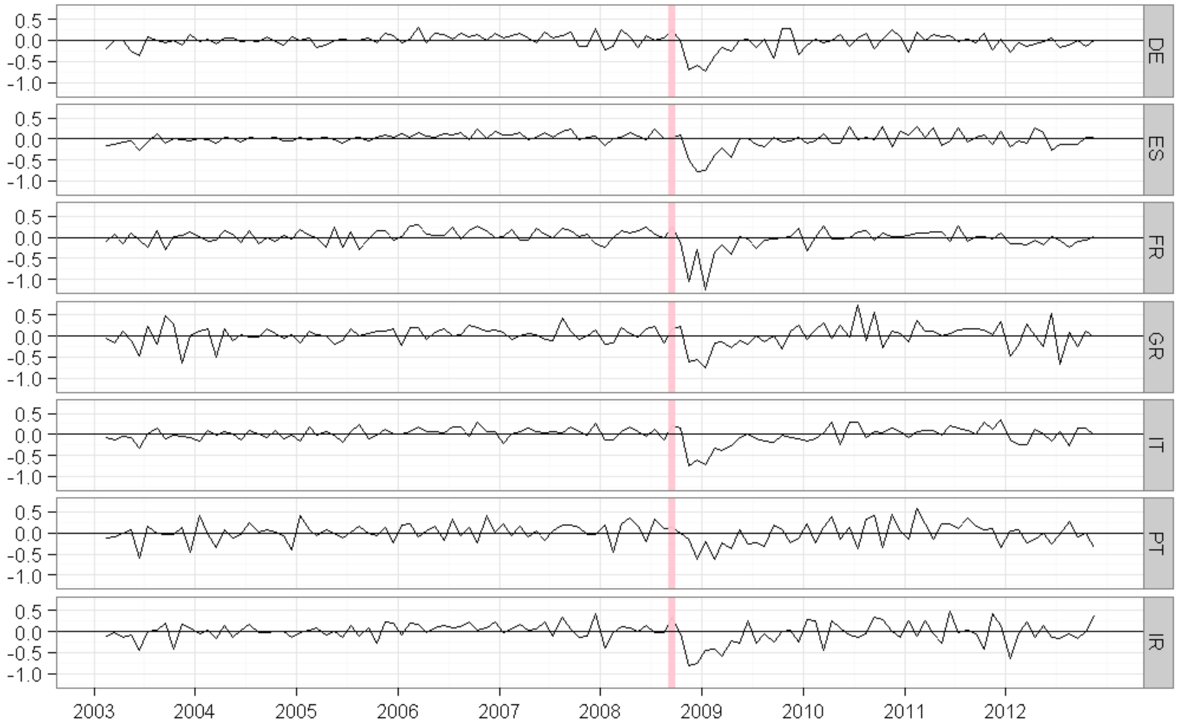
Appendix

Figure A.1: Changes in the MFIs short-rates to NFCs.



Note : The red shaded area indicates September 2008.

Table A.1: Prior distribution

	Prior distribution
β_0	$\mathcal{N}(0, 100^2)$
β_r	$\mathcal{N}(0, 100^2)$
B	$\mathcal{N}(0, 100^2)$
δ_0	$\mathcal{U}(-20, 0)$
δ_1	$\mathcal{U}(-1,1)$
α_0	$\mathcal{U}(-20, 0)$
α_1	$\mathcal{U}(-1,1)$
W	$IW(0.5{*}I, \mathrm{k} + 2)$
σ_η^2	$IG(10^{-3}, 10^{-3})$
γ	$\mathcal{U}(0, 2)$

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