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Dynamic models for monetary transmission

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Abstract

Monetary policies, either actual or perceived, cause changes in monetary interest rates. These changes impact the economy through financial institutions, which react to changes in the monetary rates with changes in their administered rates, on both deposits and lendings.

The dynamics of administered bank interest rates in response to changes in money market rates is essential to examine the impact of monetary policies on the economy. Chong et al. (2006) proposed an error correction model to study such impact, using data previous to the recent financial crisis. Parisi et al. (2015) analyzed the Chong error correction model, extended it and proposed an alternative, simpler to interpret, one-equation model, and applied it to the recent time period, characterized by close-to-zero monetary rates.

In this paper we extend the previous models in a dynamic sense, modelling monetary transmission effects by means of stochastic processes.

The main contribution of this work consists in novel parsimonious models that provide endogenously determined and generalizable models. Secondly, this paper introduces a predictive performance assessment methodology, which allows to compare all the proposed models on a fair ground.

From an applied viewpoint, the paper applies the proposed models to different interest rates on loans, showing how the monetary policy

differentially impacts different types of lendings.

Keywords: Forecasting Bank Rates, Monte Carlo predictions, Stochastic Processes.

1 Introduction

Monetary policies, such as variations in the official rate or liquidity injections, cause changes in monetary interest rates. These changes impact the economy mainly in an indirect way, through financial institutions, which react to changes in the monetary rates with changes in their administered rates, on both deposits and lendings.

The dynamics of administered bank interest rates in response to changes in money market rates is essential to examine the impact of monetary policies on the economy. This dynamics has been the subject of an extensive literature; the available studies differ, depending on the used models, the period under analysis and the geographical reference.

The relationship between market rates and administered rates is a complicated one and the evidence presented, thus far, is mixed and inconclusive. Hannan and Berger (1991), for example, examine the deposit rate setting behaviour of commercial banks in the United States and find that (a) banks in more concentrated markets exhibit greater rates rigidity; (b) larger banks exhibit less rates rigidity; and (c) deposit rates are more rigid upwards than downwards. Scholnick (1996), similarly, finds that deposit rates are more rigid when they are below their equilibrium level than when they are above; his finding on lending rate adjustment, however, is mixed. Heffernan (1997) examines how the lending and deposit rates of four banks and three building societies respond to changes in the base rate set by the Bank of England and finds that (a) there is very little evidence on the asymmetric nature of adjustments in both the deposit and lending rates, (b) there is no systematic difference in the administered rate pricing dynamics of banks and building societies, and (c) the adjustment speed for deposit rates is, on average, roughly the same as that for loan rates.

More recent papers on the same issue include: Ballester et al. (2009), Chong et al. (2006), Demirguc-Kunt and Huizinga (1999), Flannery et al. (1984), Maudos et al. (2004), Maudos et al. (2009).

The empirical evidence contained in all the previous papers can be sum-

marized in the following points: (a) bank rates react with a partial and delayed change to changes in the monetary rates; (b) the speed and the degree to which they follow these changes present substantial differences between the various categories of banking products and between different countries.

The previous conclusions have been obtained for a relatively stable time period, previous to the emergence of the recent financial crisis.

After 2008, however, they have witnessed substantial changes. From a macroeconomic viewpoint, monetary interest rates are now, in most developed economies, close to zero, or negative; from a microeconomic viewpoint, bank management has changed substantially, for the compression of interest margins and for the increase in regulatory capital requirements. The effects of the previous changes on the transmission of monetary policies have not been yet fully investigated. In particular, the current state of close-to-zero interest rates is of particular relevance, and, to our knowledge, Parisi et al. (2015) is the only paper that has concentrated on this topic, in a classical (static) linear regression framework.

The aim of this paper is to broaden the model of Parisi et al. (2015), introducing a time dynamics able (a) to capture the evolving relationship between bank rates and monetary rates and (b) to provide better results in terms of predictions.

We anticipate that static linear models perform quite well in a predictive sense, but stochastic processes are superior in terms of predictive performance, and, therefore, represent a valid alternative. Moreover, they are endogenous, and, thus, that they can be derived, estimated and predicted independently from other variable. As underlined before, this feature can be particularly useful in the current situation of almost-zero monetary rates.

Secondly, the paper demonstrates that stochastic processes maintain a good predictive performance when applied to different categories of lending activities, because of their ability to dynamically adapt to the regime switching context of the recent years.

The proposed methods are applied to data from the recent period (1999-2014), of a southern European country characterized by a traditional banking sector: Italy.

The effect of monetary policies is studied for four categories of loans: (a) loans to non-financial corporates up to 1 Mln euros; (b) loans to non-financial corporates over 1 Mln euros; (c) loans to households for credit consumption; (d) loans to households for mortgages.

The paper is structured as follows. Section 2 describes the proposed mod-

els and, in particular: Section 2.1 describes the Parisi et al. model; Section 2.2 introduces the new proposed models, with Subsection 2.2.1 concentrating on simple, univariate linear models, Subsection 2.2.2 describing stochastic processes and Subsection 2.2.3 comparing all the previous models. Section 2.3 provides the predictive performance environment used to compare the models. Section 3 shows the empirical evidence obtained from the application of the models and, in particular: Section 3.1 describes the available data; Section 3.2 presents the estimation results obtained when the models are applied to such data; Section 3.3 compares the models in a predictive sense; Section 3.4 applies stochastic processes to different types of lendings. Finally, Section 4 concludes with some final remarks.

2 Methodology

2.1 Theoretical Framework

In line with the contribution of Chong et al. (2006), the relationship between monetary rates and administered bank rates can be analyzed with the use of the Error Correction Model (ECM), following the procedure proposed by Engle and Granger (1987). The model is based on two equations. A long-run relationship provides a measure of how a change in the monetary rate is reflected in the bank rate. A short-run equation, which includes an error correction term, analyzes variations of the administered interest rates as a function of variations in the monetary rates.

Parisi et al. (2015) analyzed and extended Chong et al. (2006), by computing their two equations separately and by proposing an alternative one-equation model. More precisely, they assumed that bank interest rates depend on their previous level when monetary rates are close to zero, in order to allow for a slow and partial reaction of bank rates to monetary rates changes. Thus, they modeled bank administered interest rates as a function of monetary rates, their variations and the previous level of bank rates. Their complete model, that in the next Sections will be called the *Parisi et al. model*, can be formalized as follows:

$$BR_t = k + \beta \cdot MR_{t-1} + \gamma \cdot \Delta MR_t + \delta \cdot BR_{t-1} + \epsilon_t. \quad (2.1)$$

In equation (2.1) BR_t and MR_t represent, respectively, the bank administered rates and the monetary rates at time t ; β is a regression coefficient

that gives a measure of the extent of the monetary rate transmitted on bank rates in a long-term perspective; γ is the coefficient that explains the influence of the variations of monetary rates on the bank rates levels; δ weights the auto-regressive component BR_{t-1} ; k is a constant that synthetizes all other factors that, in addition to the dynamics described by the regressors, may affect the transmission mechanism of the monetary policy on bank rates as, for example, the market power and the efficiency of a bank; finally, ϵ_t is the error term.

The previous linear model can be equivalently written in terms of the variations of the administered rates:

$$\Delta BR_t = k + \beta \cdot MR_{t-1} + \gamma \cdot \Delta MR_t + (\delta - 1) \cdot BR_{t-1} + u_t. \quad (2.2)$$

The previous formulation is necessary in order to make all models comparable.

2.2 The proposed models

2.2.1 Univariate Linear Models

The Parisi et al. (2015) model can be written in terms of either the level of bank interest rates (2.1) or their variations (2.2): for this reason the first objective of our analysis consists in understanding how they both depend on the levels or on the variations of monetary rates. The two equations can be formalized as two simpler, univariate regression models, as follows:

$$BR_t = k + \beta \cdot MR_t + \epsilon_t; \quad (2.3)$$

$$\Delta BR_t = k + \beta \cdot \Delta MR_t + u_t. \quad (2.4)$$

While model (2.3) explains the levels of bank rates in terms of the level of monetary ones, equation (2.4) is a model for the variations of bank rates in terms of the variations of monetary rates. These models, albeit very simple, should be considered in practical applications, because (a) they give insights on the relationship between the two variables considered in this paper; (b) it is interesting to understand which one of the two equations is more significant during the recent time-period and (c) it is of interest to see how the significance of the two models changes over time.

2.2.2 Linear Models and Stochastic Processes

The model proposed by Parisi et al. (2015) and described in Section 2.1 can be simplified by slightly changing the initial assumptions: by considering that monetary rates are at the moment very close to zero, we can relax equation (2.2) and make it independent from the level of monetary rates. The result is the following:

$$\Delta BR_t = k + \delta BR_{t-1} + \gamma \Delta MR_t + u_t. \quad (2.5)$$

In order to make it comparable with the other models we can write equation (2.5) in terms of the levels of administered rates:

$$BR_t = k + (\delta + 1)BR_{t-1} + \gamma \Delta MR_t + \epsilon_t. \quad (2.6)$$

In the next Sections, equations (2.5) and (2.6) will be called the *Proposed linear model*.

Furthermore, according to the existing literature, we can consider the variations of monetary rates as a Wiener process: they can thus be used in order to represent the Brownian motion dW_t . Consistently with this method we can write (2.5) in the alternative way:

$$\Delta BR_t = k + \delta BR_{t-1} + \sigma \epsilon_t. \quad (2.7)$$

The obtained result is particularly interesting: (2.7), in fact, corresponds to the discrete version of the Vasicek stochastic process, with $k + \delta BR_{t-1}$ being the drift term, σ representing the volatility of the process and $\epsilon_t \sim N(0, 1)$ corresponding to the geometric Brownian motion dW_t of the continuous-time equation.

Moreover, the linear regression model described in (2.5) can be extended in a Cox-Ingersoll-Ross (CIR) stochastic process, whose discrete-time version can be expressed by the following:

$$\Delta BR_t = k + \delta BR_{t-1} + \sigma \sqrt{BR_{t-1}} \epsilon_t, \quad (2.8)$$

where, again, $\epsilon_t \sim N(0, 1)$ corresponds to the geometric Brownian motion dW_t of the continuous-time CIR equation; $k + \delta BR_{t-1}$ is the drift term, in which $\frac{k}{\delta}$ represents the mean long term level of the bank administered rates, δ is the adjustment speed, while σ is the volatility.

In order to make equations (2.7) and (2.8) comparable, the latter can be written by substituting ϵ_t with the monetary rates variations, thus obtaining the discrete formulation:

$$\Delta BR_t = k + \delta BR_{t-1} + \sigma \sqrt{BR_{t-1}} \Delta MR_t + u_t. \quad (2.9)$$

Also in this case the equation can be written in terms of the levels of bank administered interest rates, and the result is the following:

$$BR_t = k + (\delta + 1)BR_{t-1} + \sigma \sqrt{BR_{t-1}} \Delta MR_{t-1} + \epsilon_t. \quad (2.10)$$

In this way we have obtained two equations, (2.9) and (2.10), that can be compared with (2.5) and (2.6).

Finally, the two discrete formulations (2.7) and (2.8) can be interpreted as two specific solutions of the general family of non-parametric, time-homogeneous and continuous models:

$$d BR_t = (k - \delta BR_{t-1}) dt + \sigma (BR_{t-1})^\beta d W_t, \quad (2.11)$$

where $\beta = 0.5$ corresponds to the CIR process, while $\beta = 0$ represents the Vasicek model. Because of their large diffusion in many application, in Section 3 we will concentrate on both the Vasicek and the CIR specifications of the stochastic process (2.11), and we will consider their continuous versions with respect to their discrete formulations.

2.2.3 Model comparison

If we consider the second formulation of the Parisi et al. model (2.2), we can compare it with the proposed models (2.5) and (2.9).

The first way of comparing models consists in comparing their coefficients. More formally, by using the notational index 1 for the coefficients of the Parisi et al. model, and the index 2 for the coefficients referred to the proposed linear model (2.5), the second one is a particular case of the first one with the following constraints on the parameters:

$$\begin{cases} k^1 = k^2, \\ \gamma^1 = \gamma^2, \\ \delta^1 = \delta^2 + 1, \\ \beta^1 = 0. \end{cases} \quad (2.12)$$

The last equation in (2.12) is particularly interesting because it means that model (2.5) can be derived by (2.2) by eliminating the dependence on the level of monetary rates. Unfortunately, the CIR formulation (2.9) can not be compared with the other models because of the presence of the volatility term, which is a function of $\sqrt{BR_{t-1}}$.

A full comparison of our proposed models with the Parisi et al. model can not be easily carried out in a statistical testing framework, as the models are, evidently, not nested; however, they can be compared also in terms of their predictive performance and, for this purpose, the next Subsection introduces an appropriate methodology.

Finally, a third comparison between the three models can be carried out by looking at their time dynamics. This is of particular interest in the context of interest rate risk modeling. For sake of simplicity we illustrate this comparison for the first three one-month rates and, then, for the general situation.

Thus, assume that:

$$\begin{cases} BR(0)^{\{1,2,3\}} = BR_0^{\{1,2,3\}}, \\ MR(0)^{\{1,2,3\}} = MR_0^{\{1,2,3\}}. \end{cases}$$

By using the same notation as before (index 1 for the Parisi et al. model (2.1), index 2 for the proposed linear model expressed by (2.6), and index 3 for the CIR discrete model (2.10)), and by considering the equations that derive the levels, rather than the variations, of bank rates, for the first month ahead and for the Parisi et al. model we obtain:

$$BR_1^1 = MR_0^1\beta^1 + \Delta MR_1^1\gamma^1 + BR_0^1\delta^1 + k^1,$$

whereas for the second and the third month ahead:

$$BR_1^1 = MR_0^1\beta^1(1+\delta^1) + \Delta MR_1^1[\beta^1 + \delta^1\gamma^1] + \Delta MR_2^1\gamma^1 + BR_0^1(\delta^1)^2 + k^1(1+\delta^1);$$

$$\begin{aligned} BR_3^1 &= MR_0^1\beta^1(1 + \delta^1 + (\delta^1)^2) + \Delta MR_1^1[\beta^1 + \delta^1(\beta^1 + \delta^1\gamma^1)] + \\ &+ \Delta MR_2^1[\beta^1 + \delta^1\gamma^1] + \Delta MR_3^1\gamma^1 + BR_0^1(\delta^1)^3 + k^1\delta^1(1 + \delta^1). \end{aligned}$$

For the proposed linear model (2.6), again assuming as initial values BR_0^2 and MR_0^2 , we find the following equations for the first, the second and the third months ahead:

$$BR_1^2 = \Delta MR_1^2 \gamma^2 + BR_0^2(1 + \delta^2) + k^2;$$

$$BR_2^2 = \Delta MR_1^2[\gamma^2(1 + \delta^2)] + \Delta MR_2^2 \gamma^2 + BR_0^2(1 + \delta^2)^2 + k^2(2 + \delta^2);$$

$$BR_3^2 = \Delta MR_1^2[\gamma^2(1 + \delta^2)^2] + \Delta MR_2^2[\gamma^2(1 + \delta^2)] + \\ + \Delta MR_3^2 \gamma^2 + BR_0^2(1 + \delta^2)^3 + k^2(1 + (2 + \delta^2)(1 + \delta^2)).$$

Finally, for the discrete CIR model (2.9) expressed in terms of the levels of bank interest rates the results are the following:

$$BR_1^3 = (\delta^3 + 1)BR_0^3 + \sigma^3 \sqrt{BR_0^3 \Delta MR_1^3},$$

$$BR_2^3 = \Delta MR_1^3 \sigma^3 (\delta^3 + 1) \sqrt{BR_0^3} + \Delta MR_2^3 \cdot \sigma^3 \sqrt{(\delta^3 + 1)BR_0^3 + \sigma^3 \sqrt{BR_0^3 \Delta MR_1^3} + k^3} + \\ + BR_0^3 (\delta^3 + 1)^2 + k^3 (\delta^3 + 2),$$

$$BR_3^3 = \Delta MR_1^3 \sigma^3 (\delta^3 + 1)^2 \sqrt{BR_0^3} + \\ + \Delta MR_2^3 \cdot \sigma^3 (\delta^3 + 1) \sqrt{(\delta^3 + 1)BR_0^3 + \sigma^3 \sqrt{BR_0^3 \Delta MR_1^3} + k^3} + \\ + \Delta MR_3^3 \cdot \sigma^3 \sqrt{\Delta MR_1^3 \sigma^3 (\delta^3 + 1) \sqrt{BR_0^3} + MR_2^3 \cdot \sigma^3 \sqrt{(\delta^3 + 1)BR_0^3 + \sigma^3 \sqrt{BR_0^3 \Delta MR_1^3} + k^3} + k^3 (\delta^3 + 2)}$$

From the above calculations we can derive a general iterative formula for the three models, in order to calculate bank interest rates at any time t ($BR_t^{\{1,2,3\}}$), as functions of the levels of bank rates at time $t - 1$ ($BR_{t-1}^{\{1,2,3\}}$).

For the Parisi et al. model (2.1) we obtain:

$$BR_t^1 = \delta BR_{t-1}^1 + \beta^2 \left[MR_0^1 + \sum_{s=1}^{t-1} \Delta MR_s^1 \right] + \gamma^1 \Delta MR_t^1 + k^1. \quad (2.13)$$

The proposed linear model, which corresponds to the discrete formulation of the Vasicek model, remains the same as expressed by equation (2.6) because it does not depend on the level of monetary rates:

$$BR_t^2 = (1 + \delta^2)BR_{t-1}^2 + \gamma^2\Delta MR_t^2 + k^2. \quad (2.14)$$

Similarly, the discrete CIR version does not depend on the levels of monetary rates, thus it remains the same as expressed by equation (2.10):

$$BR_t^3 = (1 + \delta^3)BR_{t-1} + \sigma\sqrt{BR_{t-1}}\Delta MR_t^3 + k^3. \quad (2.15)$$

Note that the second expression (2.14) is a particular case of (2.13) with the constraint $\beta^1 = 0$, which is consistent with (2.12). Finally, the CIR formulation (2.15) still remains different from the other two because of the presence of the term $\sqrt{BR_{t-1}}$.

2.3 Predictive performance assessment

All the models proposed so far are quite heterogeneous, are based on different hypothesis and present various approaches, thus a general set-up is required in order to compare them on the same playing field. This can be provided, for example, by a predictive performance framework that we are going to illustrate in this Subsection. Doing so, we can enrich all the models with a validation procedure that has been firstly introduced by Parisi et al. (2015).

In order to predict bank rates, we need to estimate reasonable future values of monetary rates. Consistently with the literature, we assume that their variations follow a Wiener process.

More formally, assume that we want to predict the level of monetary rates for each of the next 12 months. Let $\widehat{\Delta MR}_i$ indicates the variation of the monetary rate in a given month. We then assume that all the $\widehat{\Delta MR}_i$ are independently and identically distributed Gaussian random variables, so that:

$$\begin{cases} \widehat{\Delta MR} \sim N(0, \sigma^2) \\ \widehat{MR}_i = \widehat{MR}_{i-1} + \widehat{\Delta MR}_i \quad i = 1, \dots, 12. \end{cases} \quad (2.16)$$

Equation (2.16) describes a recursive procedure to obtain predictions of the monetary rates for a given year ahead, based on the Wiener process assumption. We can then insert the predicted monetary rates as regressor values in the models of the previous Subsection and, thus, obtain predictions for the administered bank rates.

2.3.1 Univariate Linear Models

The two univariate linear models are quite easy to be predicted, and the corresponding equations are:

$$\begin{cases} \widehat{BR}_i = k + \beta \cdot \widehat{MR}_i, \\ \widehat{\Delta BR}_i = \widehat{BR}_i - \widehat{BR}_{i-1}; \end{cases}$$

$$\begin{cases} \widehat{\Delta BR}_i = k + \beta \cdot \widehat{\Delta MR}_i, \\ \widehat{BR}_i = \widehat{BR}_{i-1} + \widehat{\Delta BR}_i, \end{cases}$$

where $\widehat{\Delta MR}_i$ and \widehat{MR}_i are estimated according to equation (2.16)

2.3.2 Linear Models and Stochastic Processes

The proposed linear model, described in (2.6), can be used in order to predict future values for bank administered interest rates as follows:

$$\widehat{BR}_i = k + \gamma \cdot \widehat{\Delta MR}_i + (\delta + 1) \cdot \widehat{BR}_{i-1}.$$

In the previous Section we have described linear models as the discrete versions of a Vasicek and a CIR process: in the next Section, however, we will consider them in their continuous formulation, as described by equation (2.11).

If the parameters of the linear time-homogeneous regression models presented in this paper can be estimated by means of ordinary least squares, the two stochastic time-homogeneous continuous processes need a specific parameter estimation.

The three parameters k , δ and σ of the Vasicek process can be calculated through the maximization of the log-likelihood function: according to the literature this procedure is standard practice, and it aims at finding the values of the parameters that maximize the probability of the observed outcome. In order to derive the likelihood function, two variables have to be defined:

$$\text{Var}_t = \frac{\sigma^2}{2\delta}(1 - e^{-2\delta\Delta t}), \quad \nu(BR_t, BR_{t+1}, \Delta t) = \frac{BR_{t+1} - [\frac{k}{\delta} + (BR_t - \frac{k}{\delta})e^{-\delta\Delta t}]}{\sqrt{\text{Var}_t}}.$$

Thus the log-likelihood function can be derived:

$$\log \ell(K) = -\frac{N-1}{2} \log 2\pi - \frac{N-1}{2} \log \left(\frac{\sigma^2}{2\delta} (1 - e^{-2\delta\Delta t}) \right) - \frac{1}{2} \sum_{t=1}^{T-1} \nu^2(BR_t, BR_{t+1}, \Delta t). \quad (2.17)$$

The parameters' vector \hat{K} can be easily found by maximizing the previous equation:

$$\hat{K} = (\hat{k}, \hat{\delta}, \hat{\sigma}) = \arg \max_K \log \ell(K). \quad (2.18)$$

The parameters estimation of the CIR process is based on the same maximization procedure. Firstly, the following variables have to be defined:

$$c = \frac{2\delta}{\sigma^2(1 - e^{-\delta t})}, \quad u = cBR_t e^{-\delta t}, \quad q = \frac{2k}{\sigma^2} - 1, \quad v = cBR_{t+1}.$$

Then, the log-likelihood function of the process can be derived:

$$\log \ell(K) = (N-1) \log c + \sum_{t=1}^{T-1} \left[-u_t - v_t + \frac{q}{2} \log \left(\frac{v_t}{u_t} \right) + \log [I_q(2\sqrt{u_t v_t})] \right], \quad (2.19)$$

where $I_q(2\sqrt{uv})$ is the modified Bessel function of order q . The parameter vector \hat{K} is again found by maximizing the log-likelihood function:

$$\hat{K} = (\hat{k}, \hat{\delta}, \hat{\sigma}) = \arg \max_K \log \ell(K). \quad (2.20)$$

Once the parameters have been estimated, through the Monte Carlo estimation procedure described in the next paragraph and by considering the variations of monetary rates as a Wiener process, a number of scenarios is generated in order to predict future values for the bank administered interest rates, both for the Vasicek and the CIR equations.

2.3.3 Monte Carlo estimation

According to the standard cross-validation (backtesting) procedure, to evaluate the predictive performance of a model, we can compare, for a given time period, the predictions of monetary rates obtained with the previous

equations with the actual values. To obtain a robust measurement we can indeed generate N scenarios of monetary rates, using (2.16), and obtain the corresponding bank rates, using either (2.1), (2.6) or (2.10). On the basis of them we can calculate and approximate Monte Carlo expected values and variances of the predictions, as follows.

Let Y be a bank rate to be predicted at time i , with unknown density function $f_Y(y)$. The expected value of Y can then be approximated with

$$\widehat{\mathbb{E}(Y)} = \frac{1}{N} \sum_{k=1}^N y^{(k)}, \quad (2.21)$$

and its variance with

$$\widehat{var}(Y) = \frac{1}{N^2} \sum_{k=1}^N [y_i - \widehat{E}(Y)]^2. \quad (2.22)$$

A similar procedure can be obtained by considering Y as a bank rate variation, rather than a bank rate level.

In the next section we will use (2.21) and (2.22) to compare model predictive performances. Before proceeding, we would like to remark that the random number generation at the basis of the Monte Carlo algorithm is pseudo-random, and depends on an initial seed. Different seeds may lead to different results so that models can not be compared equally. We have thus decided to use the same random seed for all the proposed models, so that the differences in performances are not biased by the Monte Carlo random mechanism.

3 Data analysis and results

3.1 Descriptive analysis

The recent financial crisis has had a major impact on the banking sector and, in particular, has led to a change in the relationship between monetary and administered rates and, therefore, to the transmission mechanisms of monetary policies. In the Eurozone, characterized by one monetary authority (the European Central Bank), that regulates still fragmented national markets, this effect is particularly evident: southern european countries, differently

from what expected, have benefited very little from the drop of monetary rates that has followed the financial crisis.

To investigate the above issues we firstly focus on a southern european country, Italy, for which the transmission of monetary impulses is particularly problematic, given the importance of the banking sector and the difficult economic situation.

Accordingly, we have collected monthly time series data on monetary rates and on aggregate bank administered rates on lendings to non-financial corporates, from the statistical database provided by the Bank of Italy, for the period ranging from January 1999 to December 2014.

For the purposes of our analysis, the monetary rate used in this paper is the 3-month Euribor.

Figure 3.1 represents the time series of the chosen monetary rates, along with that of the aggregate administered bank rates on lendings, for the considered time period.

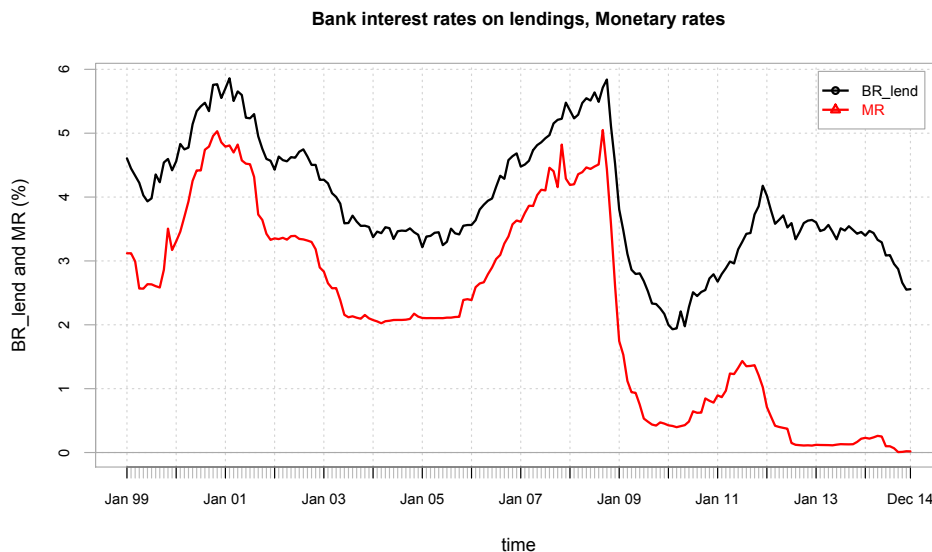


Figure 3.1: The observed monetary and administered bank rates

From Figure 3.1 note that both the administered and the monetary rates rapidly decreased in 2008 and 2009, while in the last two years they have remained quite stable, with monetary rates very close to the zero lower bound.

Moreover, the two curves seem to have the same shape between 1999 and 2010, while the relationship between the two changes in the following years, with bank rates on lending activities substantially decreasing during 2014. In other words, the correlation pattern between the bank administered rate and the monetary rate shows a very heterogeneous behavior: before 2010 they seem to have a stable relationship (both dropping in 2008); after that time monetary rates look stable and close to zero, while bank rates continue fluctuating, thus leading to a relationship between the two that is indeed quite different from the one observed before the crisis.

To obtain further insights, in Figure 3.2 the histogram and the corresponding density estimate of the two rates are presented.

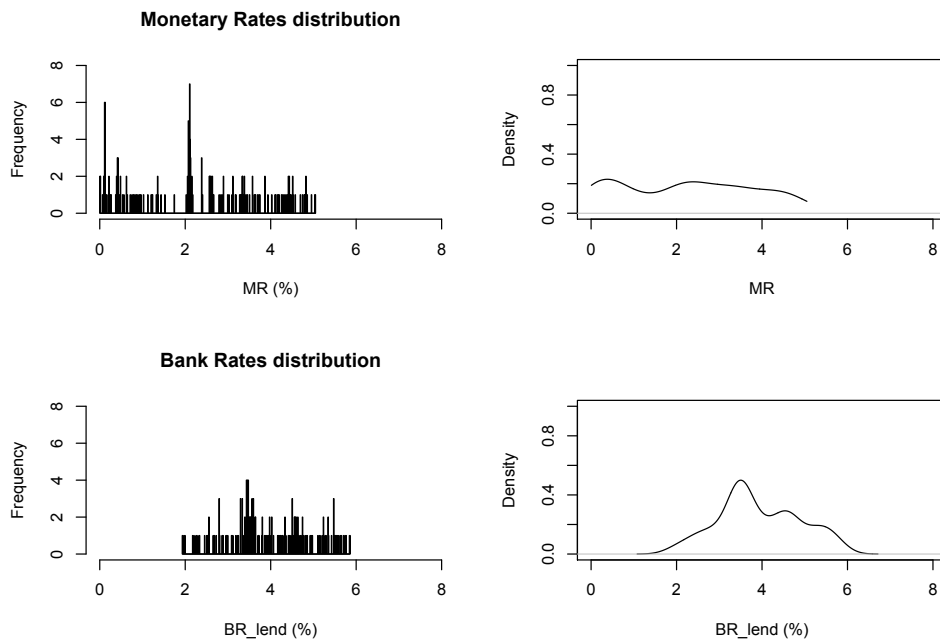


Figure 3.2: Distribution of the monetary and the administered bank rates

Figure 3.2 reveals that bank administered interest rates are more concentrated around their mean value, while monetary rates are quite spread.

It is also interesting to compare the distributions of the variations of the two rates, represented in Figure 3.3.

From Figure 3.3 note that the variations of monetary rates are more concentrated around zero, while bank administered interest rates seem to have

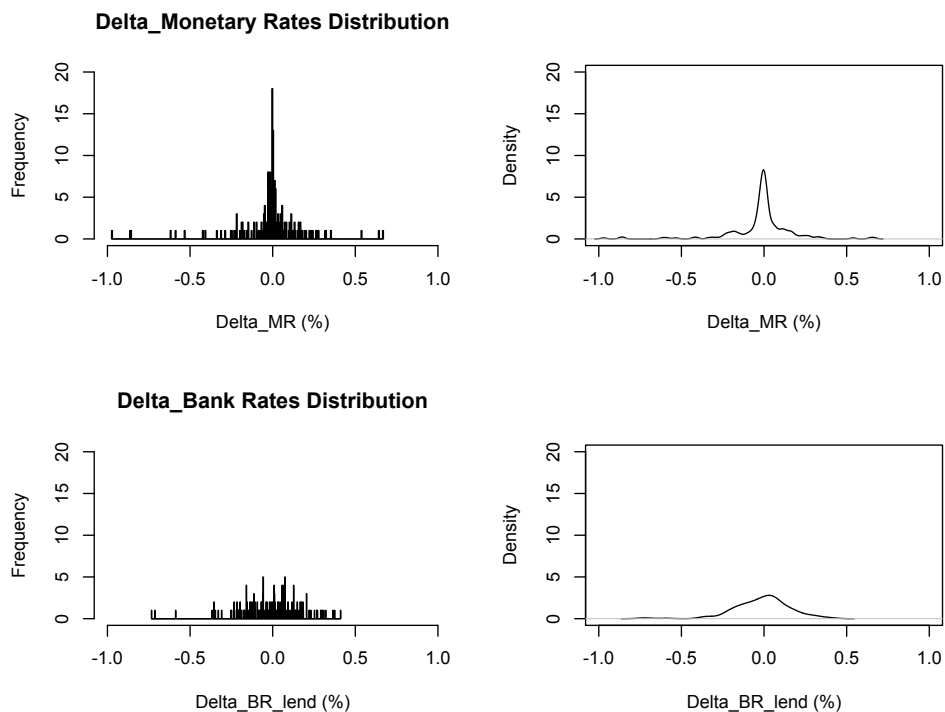


Figure 3.3: Distribution of the variations of monetary and administered bank rates

broader variations. Indeed, the behavior of ΔMR justifies the assumption of considering the variations of monetary interest rates as a Wiener process, so that they can be modeled according to equation (2.16). For the same reason we can consider the linear model proposed in Section 2.2.2 as the discrete version of a stochastic process, thus justifying the use of Vasicek and CIR stochastic differential equations.

We have previously commented on the change in the relationship between the two rates, comparing the situation before and after 2009. This switching behavior can be easily seen by looking at the correlation matrix between the rates and their variations. Table 3.1 shows the correlations between the rates and between their variations in the two periods (1999-2008) and (2009-2014), before and after the financial crisis.

From Table 3.1 note that the correlation between the levels of bank and monetary rates is significantly positive during the whole period (1999 - 2014):

	1999 - 2008	2009 - 2014	1999 - 2014
BR, MR	0.970	0.043	0.889
$\Delta BR, \Delta MR$	0.536	0.584	0.543

Table 3.1: Correlation matrix between rates and their variations, in different periods

furthermore, by looking at the decomposition in the two time periods, it is clear that the relationship between the two is strongly positive during the first, more stable time-window, while bank rates and monetary rates become uncorrelated in the following years. The correlation between the variations of the administered bank rates and those of the monetary rates, instead, has remained almost the same during the different years considered in this analysis.

3.2 Model estimates

For the models proposed in Section 2.2, we now show the corresponding parameter estimates, considering the following four time series: (a) data from 1999 to 2007; (b) data from 1999 to 2008; (c) data from 2009 to 2013; (d) data from 1999 to 2013. This choice of data windows is consistent with the aim of investigating the switching behavior in the correlation structure of interest rates, which has occurred during the years 2008 and 2009. On the basis of this windows selection we intend to obtain predictions for the years 2008, 2009 and, finally, for the last available year, 2014. Predictions can be compared with the actual occurred value, thus giving a measure of model predictive performance through an out-of-sample analysis.

We now show the parameter estimates for all the considered models, including the two simple univariate linear models, and for the four periods we have chosen. For each linear model estimate we also report the corresponding t - value and the R^2 contribution.

3.2.1 Univariate Linear Models

Table 3.2 shows the parameter estimates for the simple univariate linear model expressed in terms of the levels of bank interest rates (2.3).

Consistently with the correlation matrix (Table 3.1), the parameter β has decreased after 2008, becoming not significant during the third period

	1999 - 2007		1999 - 2008		2009 - 2013		1999 - 2013	
	Coeff.	<i>t</i>	Coeff.	<i>t</i>	Coeff.	<i>t</i>	Coeff.	<i>t</i>
<i>k</i>	1.918	32.73	1.889	30.89	3.086	23.80	2.651	43.08
β	0.766	43.00	0.783	43.51	-	-	0.565	25.79
R^2	0.946		0.941		0.0002		0.789	

Table 3.2: Parameter estimates for the univariate linear model in terms of the levels of bank interest rates

(2009-2013); similarly, the R^2 contribution has consistently dropped in the recent years, making the whole regression model not significant during the years 2009-2013. This is a clear evidence of the fact that, when monetary rates are close to zero as in the current situation, the relationship between bank administered interest rates and monetary rates radically changes, emphasizing the need of a more sophisticated model able to capture the dynamic dependence between the two.

Table 3.3 shows the parameter estimates for the univariate linear model in terms of the variations of bank interest rates (2.4).

	1999 - 2007		1999 - 2008		2009 - 2013		1999 - 2013	
	Coeff.	<i>t</i>	Coeff.	<i>t</i>	Coeff.	<i>t</i>	Coeff.	<i>t</i>
<i>k</i>	-	-	-	-	-	-	-	-
β	0.334	4.354	0.419	6.873	0.700	5.767	0.475	8.706
R^2	0.153		0.288		0.364		0.300	

Table 3.3: Parameter estimates for the univariate linear model in terms of the variation of bank interest rates

From Table 3.3 it is clear that the univariate linear model for the variations of administered bank interest rates, calculated as a function of the variations of monetary rates, shows different results: first of all, the intercept term is not significant; secondly, R^2 values are quite low during all the periods considered in the analysis; finally, the coefficient β shows an opposite trend with respect to the parameter β of Table 3.2, strongly increasing after 2008. These results are a further confirmation of the changing regime after 2009.

3.2.2 Linear Models and Stochastic Processes

Table 3.4 shows the parameter estimates for the linear model (2.6) that has been proposed in Section 2.2.2. In order to be consistent with the other models and their estimated parameters, in Table 3.4 are reported the coefficients of the equation that explains bank administered interest rates as a function of their previous levels and of the variations of monetary rates. The notation is thus consistent with equation (2.6).

	1999 - 2007		1999 - 2008		2009 - 2013		1999 - 2013	
	Coeff.	t	Coeff.	t	Coeff.	t	Coeff.	t
k	-	-	-	-	-	-	-	-
γ	0.333	4.315	0.414	6.721	0.693	5.022	0.472	8.587
$\delta + 1$	0.993	52.631	0.991	56.206	0.996	28.610	0.993	85.960
R^2	0.964		0.965		0.941		0.977	

Table 3.4: Parameter estimates for the proposed linear model

Table (3.4) shows that our proposed linear model presents an interesting behavior. Firstly, the regression model is strongly significant during all the periods considered. Secondly, the autoregressive component seems the most explicative one, again for the four time-periods. Finally, the coefficient γ , which links bank rates to the variations of monetary rates, increases during the last years 2009 - 2013.

Table 3.5 shows the parameter estimates for the two stochastic processes introduced in Section 2.2.2 as the continuous-time versions of the previous linear model.

	Vasicek				CIR			
	1999-2007	1999-2008	2009-2013	1999-2013	1999-2007	1999-2008	2009-2013	1999-2013
k	0.009	0.112	0.134	0.062	0.051	0.105	0.124	0.061
δ	0.001	0.025	0.045	0.017	0.010	0.024	0.042	0.017
σ	0.150	0.172	0.158	0.175	0.071	0.079	0.091	0.087

Table 3.5: Parameter estimates for the two stochastic processes: Vasicek and CIR

Table 3.5 presents, in the first four columns, the estimated coefficients for the Vasicek model (equation (2.11) with $\beta = 0$), consistently with the four selected time-periods. Similarly, the last four columns refer to the CIR stochastic process (equation (2.11) with $\beta = 0.5$).

From a comparison between these results it is clear that the drift terms of the two models are quite similar to each other: moreover, the drift term of both models increases during the last two periods, making it more significant with respect to the volatility term.

Finally, it is interesting to compare the coefficient σ obtained with the Vasicek and the CIR processes: this, in fact, is much higher for the Vasicek model with respect to the CIR specification of equation (2.11): the reason for this behavior is due to the fact that the volatility term in the Vasicek model has to compensate the absence of the multiplier $\sqrt{BR_{t-1}}$ in the second part of its equation.

Finally, in both models such a volatility is almost stable during the whole period, meaning that bank administered interest rates, in general, radically change over time.

3.3 Predictive performances

After having estimated the coefficients of the different models, we then predict monthly administered bank interest rates and their variations for 2008, 2009 and 2014, using a range of monetary rates scenarios, simulated from a Wiener process as previously described. In particular, for the 2014 predictions, we performed the simulations by using the coefficients obtained both by considering the whole period (1999-2013) and the second part of the time range under examination (2009-2013). In the next Figures the estimated variations of bank administered interest rates are illustrated.

Firstly, in Figure 3.4 a comparison between the predictions for 2014 (data from 1999 until 2013) obtained with the two simple, univariate linear models (2.3) and (2.4) is shown.

From Figure 3.4 it is clear that the predicted values of the variations of bank administered rates (blue) are quite stable and homogeneous over time, and they are not able to capture the changing behavior of the real, observed variations (red).

Secondly, in Figure 3.5 a comparison between the predictions for 2014 (data from 1999 until 2013) obtained with the the Parisi et al. model (2.2) and the proposed linear model described in (2.5) is shown.

In Figure 3.5 both the models have been considered in the formulation that derives bank interest rates variations as functions of the corresponding regressors. As in the previous case, also from Figure 3.5 one can deduce that linear models are not able to capture the changing behavior of bank interest

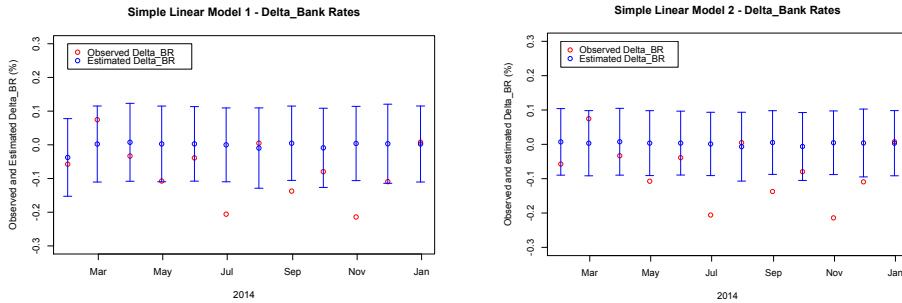


Figure 3.4: The estimated variations of administered interest rates for 2014, obtained with the two univariate linear models, by using coefficients calculated on the whole period 1999 - 2013

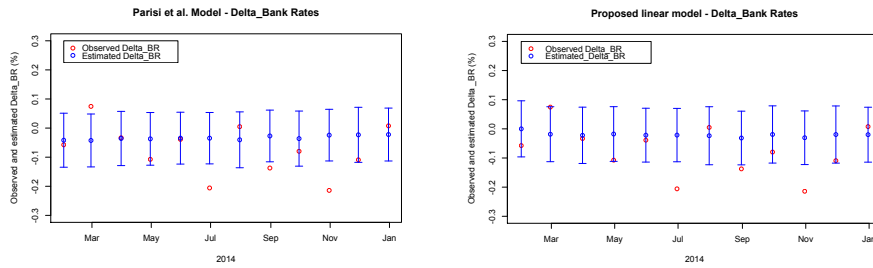


Figure 3.5: The estimated variations of administered interest rates for 2014, obtained with the Parisi et al. model and with the proposed linear model, by using coefficients calculated on the whole period 1999 - 2013

rates and of their variations, even through the dependence on monetary rates and on an autoregressive component.

Finally, in Figure 3.6 a comparison between the predictions for 2014 (data from 1999 until 2013) obtained with the two stochastic processes, Vasicek and CIR, is shown.

Figure 3.6 shows that stochastic processes better predict future values of ΔBR , even if they do not depend on other regressors or economic variables, but they are expressed as a function of a drift component (which, in turn, contains an autoregressive part), and of a volatility term. Moreover, the CIR process, because of the dependence on $\sqrt{BR_{t-1}}$ in its volatility part, seems to give better predictions with respect to the Vasicek model.

In order to verify this hypothesis, in Figure 3.7 a comparison between the

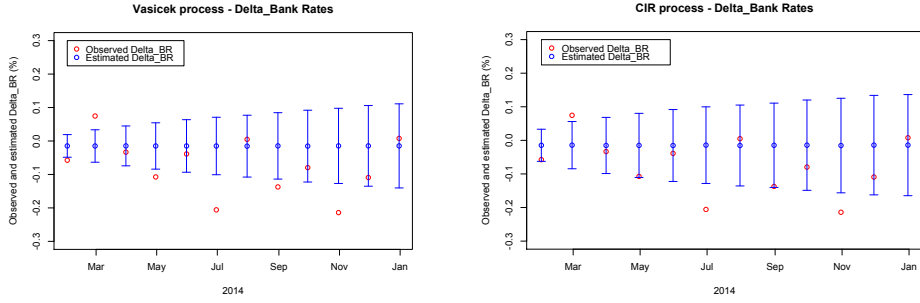


Figure 3.6: The estimated variations of administered interest rates for 2014, obtained with the Vasicek and the CIR stochastic processes, by using coefficients calculated on the whole period 1999 - 2013

predictions for 2014 of the levels of bank interest rates on lending activities, obtained with the two stochastic processes, is reported.

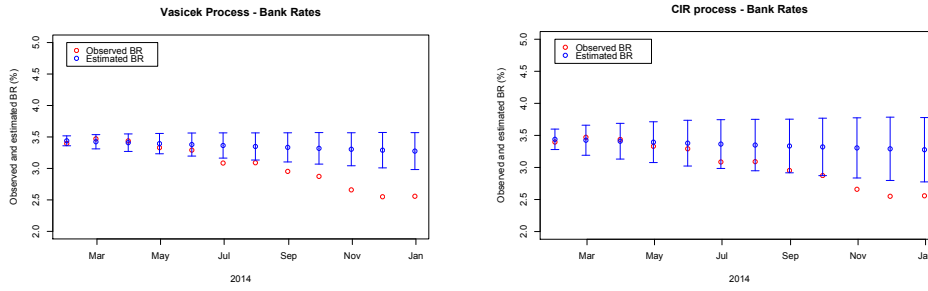


Figure 3.7: The estimated levels of administered interest rates for 2014, obtained with the Vasicek and the CIR stochastic processes, by using coefficients calculated on the whole period 1999 - 2013

Consistently with the previous observations, because the volatility term of the CIR process depends on $\sqrt{BR_{t-1}}$ and, thus, is higher than the corresponding volatility term of the Vasicek process, we can conclude that the CIR specification of equation (2.11) better predicts future values of bank rates, because its confidence intervals allow for more variations and, for this reason, can take into account the dynamic behavior of interest rates and their changing relationship.

In order to better compare models, as a measure of predictive performance we have calculated the root mean square errors of the predictions for all

the equations. Consistently with the previous Figures, here we present the prediction results in terms of variations of bank rates rather than on their levels. This because, in this case, all the predictions are more challenging, being the variations on a smaller scale.

In Table 3.6 the root mean square errors of the predicted variations of administered interest rates obtained with the two simple linear models described in (2.3) (Univariate linear model 1) and in (2.4) (Univariate linear model 2) are reported.

Model	2008 (1999-2007)	2009 (1999-2008)	2014 (2009-2013)	2014 (1999-2013)
Univariate linear model 1	0.203	0.515	0.154	0.423
Univariate linear model 2	0.300	0.342	0.120	0.254

Table 3.6: A comparison between the root mean square errors of the predictions of ΔBR (Univariate linear models)

According to the strong changes in interest rates and their variations occurred between 2008-2010, the root mean square errors are quite high for the second prediction (2009), but they remain quite large also by considering the whole period 1999 - 2013 for predicting 2014. This is, again, an evidence of the fact that simple, univariate linear model are not able to capture the changing relationship between interest rates during a regime switching context.

In Table 3.7 the root mean square errors of the predicted variations of administered interest rates obtained with the Parisi et al. model, our proposed linear model and the stochastic processes (Vasicek and CIR) are reported.

Model	2008 (1999-2007)	2009 (1999-2008)	2014 (2009-2013)	2014 (1999-2013)
Parisi et al. model	0.265	0.297	0.105	0.097
Proposed linear model	0.165	0.554	0.223	0.188
Vasicek	0.297	0.258	0.090	0.102
CIR	0.074	0.220	0.091	0.095

Table 3.7: A comparison between the root mean square errors of the predictions of ΔBR (Parisi et al. model, Proposed linear model and stochastic processes)

From the analysis of Table 3.7 some interesting conclusions emerge.

Firstly, all the models predict quite well future variations of bank interest rates, even if, during great changes as in 2009, all the root mean square errors increase.

Secondly, by comparing the Parisi et al. model and our proposed linear model, it is interesting to observe that the first one performs much better than the second one for predicting 2009; this is probably due to the fact that, during such a regime switching context, bank rates substantially depend on the levels of monetary rates, while this relationship is not necessary during relatively stable time periods (1999-2007), or when monetary rates are very close to the zero lower bound (2009-2013).

Moreover, the two stochastic processes are the best models in terms of predictive performance, especially during the last period, characterized by very low monetary rates. This means that continuous, time-homogeneous models are preferable with respect to linear models, and this has to be considered an even more important result because they are endogenous models, which means that data on monetary rates, as well as other macroeconomic variables, are not needed in order to predict future values of bank administered interest rates: we have thus shown that the endogeneity feature of stochastic processes is particularly useful in the current situation of almost-zero monetary rates.

Finally, by comparing the predictive performance of the Vasicek and the CIR process, the latter seems to be much preferable to the first one, because it can better capture the changing relationship between interest rates and their variations.

3.4 Lendings to Non-Financial Corporates and Households

3.4.1 Descriptive Statistics

According to the methodology proposed in the previous Section and to the corresponding results obtained through the application of the proposed models to aggregate interest rates on lendings to non-financial corporates, we now propose the analysis of disaggregated bank administered interest rates. More precisely, we have divided interest rates into four categories, according to the institution they refer to (non-financial corporates or households) and to the type of loan contract. In such a way we have obtained the following groups: (a) lendings to non-financial corporates up to 1 Mln euros; (b) lendings to

non-financial corporates over 1 Mln euros; (c) lendings to households for consumer credit; (d) lendings to households for mortgages. Similarly to the previous analysis, we have collected monthly time series data from the statistical database provided by the Bank of Italy: for what regards categories (a) and (c), data are available only from 2003, while for the other two they are provided from 1999. Again, the monetary rates used in this paper is the 1-month Euribor.

Figure 3.8 represents the time series of the chosen monetary rates and of the different bank rates, for the considered time period.

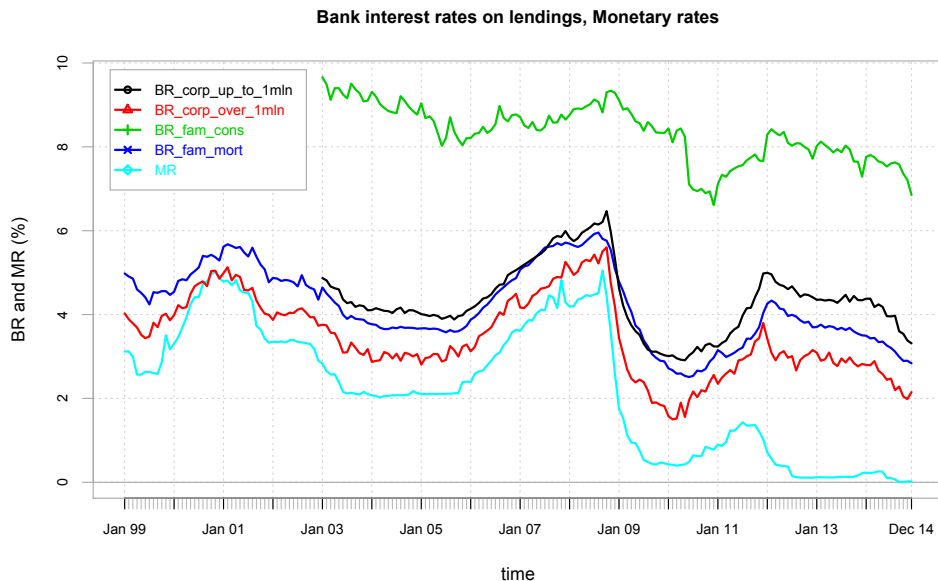


Figure 3.8: The observed monetary and administered bank rates

From Figure 3.8 note that interest rates on lendings to corporates and to households for mortgages seem to have the same behaviour, all of them dropping during 2009. A different situation is the one of lendings to households for consumer credit, whose interest rates look independent from monetary rates and from the other kinds of interest rates on lending activities.

It is also interesting to observe that the different curves represented in Figure 3.8 reflect the different amounts of risk connected to the various kinds of lending: more precisely, the riskier the loan (consumer credit), the higher the interest rate.

We have previously commented on the change in the relationship between interest rates, comparing the situation before and after 2009. This switching behavior can be easily seen by looking at the correlation matrix between all the categories of interest rates considered. Table 3.8 shows the correlations between the rates in the first period (2003-2008), while Table 3.9 considers the correlation coefficients for the following years (2009-2014).

	<i>MR</i>	<i>BR corp < 1Mln</i>	<i>BR corp > 1Mln</i>	<i>BR fam cons</i>	<i>BR fam mort</i>
<i>MR</i>	1.000				
<i>BR corp < 1Mln</i>	0.957	1.000			
<i>BR corp > 1Mln</i>	0.972	0.981	1.000		
<i>BR fam cons</i>	-0.065	0.149	0.045	1.000	
<i>BR fam mort</i>	0.972	0.989	0.979	0.079	1.000

Table 3.8: Correlation matrix between interest rates for the first period (2003-2008)

Table 3.8 shows that almost all bank administered rates are strongly and positively correlated with monetary rates, as well as they are positively correlated with each others. A different situation occurs for interest rates on lendings to households for credit consumption: this variable, in fact, is not correlated with any other interest rate, meaning that its behavior looks completely independent, according to the graph proposed in Figure 3.8

	<i>MR</i>	<i>BR corp < 1Mln</i>	<i>BR corp > 1Mln</i>	<i>BR fam cons</i>	<i>BR fam mort</i>
<i>MR</i>	1.000				
<i>BR corp < 1Mln</i>	-0.090	1.000			
<i>BR corp > 1Mln</i>	0.215	0.895	1.000		
<i>BR fam cons</i>	0.085	0.221	0.099	1.000	
<i>BR fam mort</i>	0.114	0.851	0.802	0.554	1.000

Table 3.9: Correlation matrix between interest rates for the second period (2009-2014)

Table 3.9, referred to the second time-period under analysis, somehow confirms what has been previously observed: by looking at the first column, in fact, one can notice that, during the last years, bank administered interest rates are no more correlated with monetary rates. Moreover, interest rates on lendings to corporates and to households for mortgages continue being positively and significantly related, while lendings to households for credit consumption, again, behave differently and autonomously.

3.4.2 Model Estimates

According to the results previously obtained, we now concentrate on the CIR modeling of bank administered interest rates, for which we now show the corresponding parameter estimates. For each time-period (2003-2007, 2003-2008, 2009-2013, 2003-2013) we estimate the three parameters of the CIR process described in (2.11), for each of the four categories of bank interest rates introduced in the previous Section.

	2003 - 2007			2003 - 2008			2009 - 2013			2003 - 2013		
	k	δ	σ	k	δ	σ	k	δ	σ	k	δ	σ
<i>BR corp < 1Mln</i>	0.017	0.001	0.038	0.008	0.001	0.056	0.097	0.026	0.066	0.066	0.016	0.066
<i>BR corp > 1Mln</i>	0.013	0.001	0.081	0.115	0.029	0.091	0.206	0.082	0.128	0.073	0.022	0.107
<i>BR fam cons</i>	1.554	0.179	0.068	1.440	0.164	0.067	0.927	0.121	0.085	0.466	0.058	0.075
<i>BR fam mort</i>	0.008	0.001	0.054	0.003	0.001	0.055	0.208	0.067	0.065	0.037	0.010	0.060

Table 3.10: Parameter estimates for the CIR process, for the different categories of lending activities, and for the different time windows

From Table 3.10 some interesting conclusions emerge: (a) interest rates on lendings for credit consumption behave differently from all the others, with the higher drift term during all the four time-bands; (b) the remaining three categories of lending activities seem to behave similarly, presenting similar coefficients; (c) interest rates to corporates up to 1 Mln euros look very close to interest rates to households for mortgages, according to Figure 3.8; (d) in the last period (2009-2013) all the volatility coefficients have increased, consistently with the strong fluctuations of the rates under investigation.

3.4.3 Predictive Performance

After having estimated the coefficients of the different categories of interest rates, for the different time periods, we can now predict monthly administered bank interest rates and their variations for 2008, 2009 and 2014, using a range of monetary rates scenarios, simulated from a Wiener process as previously described. In particular, in the next Figures the estimated variations of bank administered interest rates are illustrated.

In Figure 3.9 future values of the variations of bank administered interest rates on lendings to non-financial corporates, predicted for 2014, are shown: the graph on the left refers to lendings up to 1 Mln euros, while the graph on the right refers to lending activities over 1 Mln euros.

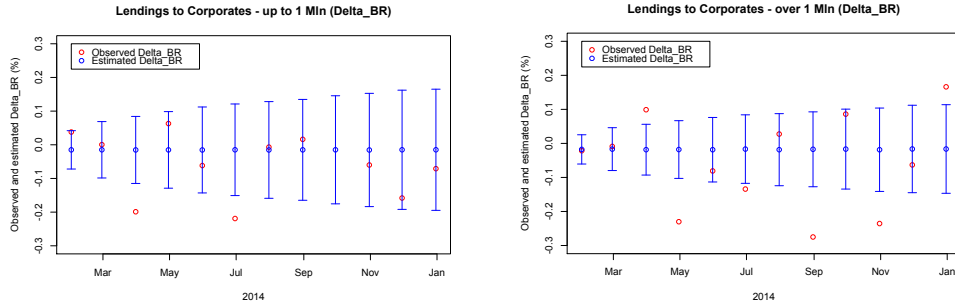


Figure 3.9: The estimated variations of bank rates on lendings to corporates, respectively up to 1 Mln euros (left) and over 1 Mln euros (right), for 2014, obtained with the CIR model by using coefficients calculated on the whole period 2003 - 2013

In Figure 3.10 estimated variations, predicted for 2014, of bank administered interest rates on lendings to households are illustrated.

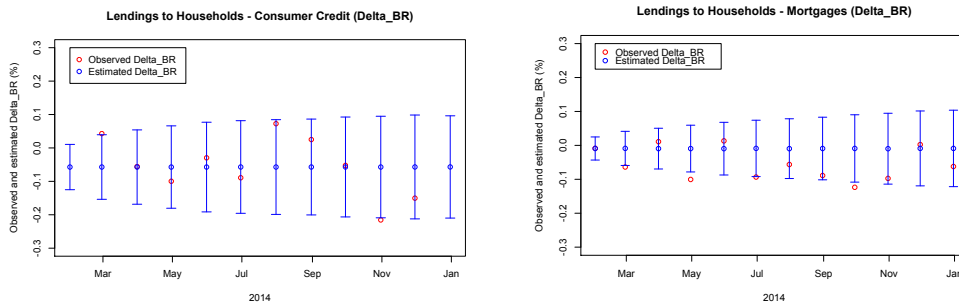


Figure 3.10: The estimated levels of bank rates to households, respectively for credit consumption (left) and for mortgages (right), for 2014, obtained with the CIR model by using coefficients calculated on the whole period 2003 - 2013

In Figure 3.10, the graph on the left refers to lendings for credit consumption, while the graph on the right refers to lending activities for mortgages.

In order to better compare the different predictions, each of them referred to a different lending activity, we have calculated the root mean square errors as a measure of predictive performance. Consistently with the previous Figures, here we present the prediction results in terms of the variations of

bank rates rather than on their levels. This because, also in this case, all the predictions are more challenging, being the variations on a smaller scale. In Table 3.11 the root mean square errors of the predicted variations of administered interest rates obtained for the four lending categories and for the different time-periods, are reported.

Model	2008 (2003-2007)	2009 (2003-2008)	2014 (2009-2013)	2014 (2003-2013)
<i>BR corp < 1Mln</i>	0.043	0.272	0.888	0.141
<i>BR corp > 1Mln</i>	0.092	0.278	0.115	0.145
<i>BR fam cons</i>	0.282	0.144	0.209	0.193
<i>BR fam mort</i>	0.093	0.207	0.047	0.066

Table 3.11: A comparison between the root mean square errors of the predictions of ΔBR , according to the lending activity they refer to

From Table 3.11 it is clear that, on average, the CIR model performs better during the first, most stable period (2003-2007) with respect to the following ones; again, lendings to households for credit consumption are the only one exception, presenting a better performance during the time-band 2003-2008. This is due to the delayed reaction of that particular kind of interest rate to changes in monetary rates and, more generally, to the financial crisis.

We can conclude that stochastic processes perform quite well, giving good results in terms of predictive performance and providing estimations consistent with real, observed data.

4 Conclusions

The main contribution of this paper is in the explanation of variations of the administered bank rates as a function of monetary rates. We propose a dynamic model, and we compare it with static linear regression models.

We have shown the implications of our proposal on data for the aggregate Italian banking sector, that concerns the recent period, characterized by a substantial shift in the relationship between monetary and bank rates, with the former getting close to zero. In this context, we have shown that stochastic processes give the best performance results and are endogenously determined: among the two stochastic processes proposed, we have demonstrated that the CIR model has to be preferable to the Vasicek specification.

Finally, we have applied the CIR process to four kinds of interest rates on lending activities: two referred to lendings to non-financial corporates (up to/ over 1 Mln euros), and two referred to lendings to households (for credit consumption and for mortgages). We have demonstrated that, also in this case, stochastic processes predict quite well future values of interest rates, being able to dynamically adapt to the regime switching context of the recent years.

Indeed, in the actual situation of almost zero monetary rates, bank interest rates are not fully explained by the monetary policy, as the latter one is no more transmitted to administered rates. Other variables, such as sovereign risk (as in Neri, 2014) may be introduced. We plan to further investigate this topic in a future research that will compare different countries in the Eurozone.

A further extension should consider the microeconomic impact of the found relationships on the probability of default of both financial and non financial corporates, enriched with a systemic correlation perspective.

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