# INTEREST RATE DYNAMICS IN KENYA: COMMERCIAL BANKS' RATES AND THE 91-DAY TREASURY BILL RATE

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## Abstract

This paper analyses the implicit dynamics underlying the interest rate structure in Kenya. For this purpose we use data on four commercial banks' interest rates (Deposits, Savings, Lending and Overdraft) together with the 91-Day Treasury Bill rate, for the time period July 1991 – August 2010, and apply various techniques based on long-range dependence and, in particular, on fractional integration. The results indicate that all series examined are nonstationary with orders of integration equal to or higher than 1 when using parametric techniques, and slightly smaller than 1 when using semiparametric methods. The analysis of various spreads suggests that Lending – Saving and Deposits – Saving are also nonstationary I(1) variables; however, the spreads vis-à-vis the Treasury Bill rate may be mean reverting if the errors are autocorrelated. The high level of dependence observed in some of these series could be the result of an incorrect interest rate policy, implying the desirability of a policy aimed at reducing interest rate volatility.

**Keywords:** Fractional integration, long-range dependence, interest rates

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## 1. Introduction

This paper examines the stochastic properties of interest rates in Kenya, shedding light on whether or not the effects of shocks are long-lived and appropriate policy actions are in order to restore equilibrium in the long run. Specifically, if the series of interest is stationary *I(0)*, shocks affecting it will have transitory effects, which disappear in the long run. On the contrary, if the series is nonstationary *I(1)*, the effects of shocks will be permanent and policy intervention will become necessary to recover their original trends. Therefore, to determine the order of integration of the series is crucial. However, in the case of interest rates the literature is very inconclusive with respect to this matter, finding empirical evidence supporting both stationarity *I(0)* and nonstationarity *I(1)*.

Interest rates play a key role at least in two very important relationships in macroeconomics, i.e., the Fisher hypothesis (FH) and uncovered interest rate parity (UIP). The former links nominal rates to expected inflation, requiring full adjustment of these two variables in the long run and implying stationarity of ex-ante real interest rates (a crucial variable for understanding investment and saving decisions as well as asset price determination). In the absence of a one-to-one adjustment, permanent shocks to either inflation or nominal rates would have permanent effects on real rates as well, which would be inconsistent with standard models of intertemporal asset pricing. If interest rates and inflation are found to be nonstationary *I(1)* processes, a long-run version of the FH can be tested within a cointegration framework (Mishkin, 1992).[1] As for UIP, stationarity of nominal short-run interest rates is required for its empirical validity. Since nominal bilateral exchange rates contain unit roots, for the UIP relation to hold nominal short-run interest rates must be mean-reverting. In the literature stationarity and mean reversion have usually been identified with *I(0)* behaviour.

[1] This literature has been extended in recent years to the case of fractional cointegration (Kasman et al., 2006; Kiran, 2013).

However, these two properties may be satisfied in cases with positive orders of integration, i.e., with *I(d)* processes with $d > 0$: stationarity holds in the *I(d)* case as long as $d < 0.5$, and mean reversion is satistied if $d < 1$. Previous empirical studies using classical *I(0)/I(1)* methods conclude in most cases that short-run interest rates have this property in Europe and in the US (e.g. Rose, 1988; Stock and Watson, 1988; Wu and Chen, 2001), providing support for the UIP relationship, but not for long-run FH. The implication for monetary policy is that central banks are constrained in their ability to set interest rates by international capital flows. In the case of the African countries such issues are even more important since their financial markets are characterised by a high level of information asymmetry and their central banks are not perceived by markets as having credibility.

The present study analyses the implicit dynamics underlying the interest rate structure in Kenya. For this purpose we use data on four commercial banks' interest rates (Deposits, Savings, Lending and Overdraft) together with the 91-Day Treasury Bill rate, for the time period July 1991 – August 2010. We focus on these variables owing to the limited data availability for this country. However, instead of carrying out standard tests based on the dichotomy between stationarity *I(0)* or nonstationarity *I(1)*, we use techniques based on long-range dependence and, in particular, on fractional integration that allows for integer as well as non-integer degrees of differentiation. Note that these commercial rates depend on the interest rates set by the central bank, whose stochastic properties in turn depend on those of the domestic and foreign shocks they are set to respond to. Therefore the nonstationarity of the commercial banks' rates could depend on inappropriate policies followed by the central bank as well as the stochastic properties of the exogenous disturbances that hit the economy combined with the inability of the central bank to offset the shocks. Consequently, to the extent that exogenous shocks and inadequate policies are not responsible for the nonstationarity of the commercial rates, an argument can be built to question Kenyan monetary policy. By contrast, the Treasury bill rate is directly related to fiscal policy and therefore analysing its stochastic properties is relevant to assess fiscal measures.

We also look at the spreads between the commercial rates. This is important to assess the effectiveness of monetary policy: nonstationary spreads hint at the inability of the central bank to keep commercial rates under tight control, since if the policies adopted by the monetary authorities were effective all such rates should follow those set by the central bank, and therefore their behaviour over time should be very similar and their differentials should be stationary variables. Such an interpretation cannot be applied in the same way to the spreads between the Treasury bill rate which, as mentioned above, is mainly driven by fiscal factors, and commercial rates which the central bank is trying to influence and are therefore, at least to some extent, affected directly by monetary policy: since the determinants of the former and the latter are not the same there is no compelling reason to expect narrow and stationary spreads; there might be a linkage only in specific policy regimes, when fiscal and monetary policy are more tightly linked (for instance, Simon (1990) reports that in the US the Treasury bill rate forecasts most accurately federal funds rates when the Fed adopts a clearly defined policy rule that does not smooth the impact of shocks on the federal funds rate). A study on this topic by Cook and Lawler (1983) finds that the spreads between Treasury bill rates and rates on private money market securities are volatile and this can be explained within a model assuming that investors can choose freely between these different type of securities; variable default-risk premia and differences in taxation appear to be the main factors affecting the spreads. Ours is in any case the first study to analyse these spreads using long memory techniques.

The outline of the paper is as follows. Section 2 briefly reviews the literature on interest rate models with *I(d)* variables, including some studies on African countries. Section 3 outlines the econometric approach employed for the analysis. Section 4 describes the data and presents the univariate results, whilst Section 5 focuses on the spreads. Section 6 offers some concluding remarks.

## 2. Literature review

A variety of interest rate models have been suggested in the literature. The crucial issue has been to determine the order of integration of the series, namely whether interest rates are stationary *I(0)* (and thus mean-reverting) or nonstationary *I(1)*. Some studies have investigated the mean reversion property of interest rates in the context of fixed income modelling – see, for example, the papers by Chapman and Pearson (2000), Jones (2003), Bali and Wu (2006), and Koutmos and Philappatos (2007) among others.

In a famous paper Rose (1988) investigated the integration properties of nominal interest rate and inflation rate using post-war data for 18 OECD countries. Conventional unit root tests did not reject the nonstationarity of interest rates, but did so for the inflation rate. This implied nonstationarity of real interest rates, which was problematic for consumption-based asset-pricing models. This controversy was partly solved using cointegration models; as Mishkin and Simon (1995) argued: "any reasonable model of the macro economy would surely suggest that real interest rates have mean reverting tendencies which make them stationary" and stationarity of interest rates is often assumed in the empirical work.

In the last two decades more attention has been paid to the possibility of long memory in interest rates. For instance, Shea (1991) investigated this issue in the context of the expectations hypothesis of the term structure. He found that allowing for the possibility of long memory significantly improves the performance of the model, even though the expectations hypothesis cannot be fully resurrected. In related work, Backus and Zin (1993) observed that the volatility of bond yields does not decline exponentially when the maturity of the bond increases; in fact, they noticed that the decline was hyperbolic, which is consistent with a fractionally integrated specification. Lai (1997) and Phillips (1998) provided evidence based on semiparametric methods that ex-ante and ex-post US real interest rates are fractionally integrated. Tsay (2000) employed an ARFIMA model and concluded that the US real interest rate can be described as an *I(d)* process. Further evidence can be found in Barkoulas and Baum (1997), Meade and Maier (2003) and Gil-Alana (2004a, b). Sun and Phillips (2004) employed a multivariate Whittle estimator and found that the order of integration of ex-post and ex-ante real interest rates as well as expected inflation is the same, with the memory parameter in the range (0.75, 1), and therefore cointegration does not hold and there is no support for a long-run Fisher relationship. On the other hand, Couchman, Gounder and Su (2006) estimated ARFIMA models for ex-post and ex-ante real interest rates in sixteen countries. Their results suggest that, for the majority of countries, the fractional differencing parameter lies between 0 and 1, and is considerably smaller for the ex-post than for the ex-ante rates.

Only a few studies on African countries exist. Nandwa (2006) examined whether nominal interest rates in a sample of Sub-Saharan countries follow stochastic trends (or unit root processes) and whether the Fisher hypothesis holds in the area. The results indicate that while the Fisher effect does not hold either for the entire sample period (1980:1 – 2005:2) or the period before the economic reforms, it does hold for the period 1995:1 -2005:2 following the economic reforms. More recently, Aboagye et al. (2008) investigated the question of the optimal spread between bank lending rates and rates that banks pay on deposits in Ghana. They found that increases in bank market power, bank size, staff costs among other factors significantly increase net interest margins, while increases in bank excess cash reserves and central bank lending rate decrease them. More evidence is available in the case of Kenya. Musila and Rao (2002) applied cointegration methods to develop a macro model for forecasting purposes. Their results suggest that the exchange rate and fiscal policy are relatively more effective in Kenya than monetary policy. Concerning specifically interest rates, they found that they are not stationary; however, there is a long-run cointegrating relationship linking money demand to real GDP and nominal interest rates. In another study, Durewall and Ndung'u (1999) proposed a dynamic model of inflation for Kenya for the time period 1974-1996, studying the stationary/nonstationary nature of several variables, including interest rates, and finding evidence of nonstationary I(1) behaviour in all cases.

Ndung'u (2000) examined the relationship between exchange rates and interest rate differentials in Kenya using a time-varying parameters approach. He finds that nominal exchange rates deviate from their long-run equilibrium level, which is given by purchasing power parity, with the deviations being determined by the interest rate differentials. Finally, in a more recent paper, Odhiambo (2009) investigated the impact of interest rate reforms on financial deepening and economic growth in Kenya. He found a positive relationship in both cases using standard (*I(0)/I(1)*) cointegration techniques. However, none of the above papers analysing African data employs fractional integration methods. By applying such techniques we allow for a much richer degree of flexibility in the dynamic specification of the series including fractional values in the degree of differentiation of the series. This will also allow us to show that in fact interest rates in a developing economy such as Kenya are non-stationary (d $\geq$

0.5) and in many cases non-mean-reverting (d ≥ 1), contrary to what is normally found in the case of the developed countries.

## 3. Econometric methodology

As already mentioned we employ methods based on long-range dependence. In particular we focus our attention on fractionally integrated or *I(d)* models. A time series $\{x_t, t = 1, 2, \ldots\}$ is said to be fractionally integrated of order *d*, and denoted by $x_t \sim I(d)$ if it can be represented as

$$(1 - L)^d x_t = u_t, \qquad t = 1, 2, \ldots, \tag{1}$$

with $x_t = 0,\ t \leq 0$,[2] where $L$ is the lag-operator ($Lx_t = x_{t-1}$): $d$ can be any real value, and $u_t$ is an $I(0)$ process, being defined as a covariance stationary process with a spectral density function that is positive and finite at any frequency. This includes a wide range of model specifications such as the white noise, the stationary autoregression (AR), moving average (MA), stationary ARMA etc.

The polynomial appearing on the left hand side in equation (1) can be defined in terms of its Binomial expansion, such that for all real *d*,

$$(1 - L)^d = \sum_{j=0}^{\infty} \frac{\Gamma(j - d)}{\Gamma(j+1)\,\Gamma(-d)} L^j,$$

where $\Gamma(x)$ is the Gamma function. For d < 0.5, it is also well known that the autocovariance function of this process $(\gamma_u)$ satisfies:

$$\gamma_u \approx c_1 u^{2d-1}, \quad as\ u \to \infty, \quad for\ |c_1| < \infty, \tag{2}$$

and, assuming that $x_t$ has an absolute continuous spectral distribution function, so that it has a spectral density function $f(\lambda)$, defined as

[2] This is a standard assumption in applied studies involving fractional integration (see the types I and II definitions of fractional integration in Gil-Alana and Hualde (2009) and Davidson and Hashimzade (2009)).

$$f(\lambda) = \frac{1}{2\pi}\left(\gamma_0 + 2\sum_{u=1}^{\infty}\gamma_u \cos(\lambda u)\right),$$

it can also be proved that

$$f(\lambda) \approx c_2 \lambda^{-2d}, \quad as\ \lambda \to 0^+, \quad for\ 0 < c_2 < \infty, \qquad (3)$$

where the symbol " ≈ " indicates that the ratio of the left-hand side and the right-hand side tends to 1, as $u \to \infty$ in (2) and as $\lambda \to 0^+$ in (3)[3] (see Granger and Joyeux, 1980; Hosking (1981), Brockwell and Davis, 1993; Baillie, 1996; etc.).

When $d = 0$ in equation (1), $x_t = u_t$, and therefore $x_t$ is $I(0)$, and possibly "*weakly autocorrelated*" (also known as "*weakly dependent*"), with the autocorrelations decaying exponentially if the underlying disturbances are autoregressive. If $0 < d < 0.5$, $x_t$ is still covariance stationary, but its lag-u autocovariance $\gamma_u$ decreases very slowly, in fact hyperbolically, according to equation (2), and therefore the $\gamma_u$ are absolutely non-summable. In that case $x_t$ is said to exhibit long memory given that its spectral density $f(\lambda)$ is unbounded at the origin (see equation (3)). Finally, it is important to note that as d in (1) increases beyond 0.5 and towards 1 (the unit root case), the variance of the partial sums of $x_t$ increases in magnitude. This is also true for $d > 1$, so a large class of nonstationary processes may be described by (1) with $d \geq 0.5$.[4] Note that this fractional integration approach is more general than the standard one which is based exclusively on integer degrees of differentiation (0 for stationarity and 1 for nonstationarity), and includes both as particular cases of interest within the AutoRegressive Fractionally Integrated Moving Average (ARFIMA) approach. The method employed in this paper to estimate the fractional differencing parameter $d$ is based on the Whittle function in the frequency domain (Dahlhaus, 1989) along with a testing Lagrange Multiplier (LM)

[3] Equation (3) requires $d < 0.5$ and $t = \ldots, -1, 0, 1, \ldots$. On the other hand, conditions (2) and (3) are not always equivalent but Zygmund (1995) and, in a more general case, Yong (1974) both give conditions under which both expressions are equivalent.

procedure developed by Robinson (1994) that allows to test the null hypothesis $H_o$: $d = d_o$ in equation (1) for any real value $d_o$, where $x_t$ can be the errors in a regression model of the form:

$$y_t = \beta^T z_t + x_t, \qquad t = 1, 2, \ldots, \tag{4}$$

where $y_t$ is the observed time series, $\beta$ is a (kx1) vector of unknown coefficients and $z_t$ is a set of deterministic terms that might include an intercept (i.e., $z_t = 1$), an intercept with a linear time trend ($z_t = (1, t)^T$), or any other type of deterministic processes. Although there exist more recent procedures to estimate parametrically d either in the time or in the frequency domain (Lobato and Velasco, 2007; Demetrescu, Kuzin and Hassler, 2008), they generally require a consistent estimate of d, and therefore the LM test of Robinson (1994) seems computationally more attractive. Moreover, the limit distribution of the estimator used here is standard normal, independently of the regressors used for zt in (4) and the type of I(0) error term ut in (1). Additionally, Gaussianity is not necessary, with a moment condition of only two being required instead. A semiparametric approach devised by Robinson (1995) will also be applied here; although other versions of this method have been suggested (Velasco, 1999; Velasco and Robinson, 2000; Phillips and Shimotsu, 2004; Shimotsu and Phillips, 2005; Abadir et al., 2007; Shimotsu, 2010), they require additional user-chosen parameters, with the estimates of d possibly being very sensitive to the choice of these parameters. In this respect, the method of Robinson (1995), which is computationally simpler, seems preferable.[5]

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[4] See Diebold and Rudebusch (1989), Sowell (1992a) and Gil-Alana and Robinson (1997) for applications involving *I(d)* processes in macroeconomic time series.

[5] In addition to the methods discussed in the text, we also employed other conventional parametric approaches such as Sowell's (1992b) and Beran's (1995) maximum likelihood methods and the results were completely in line with those reported in the paper.

## 4. Data and empirical results

The series used are from the Central Bank of Kenya database and can be downloaded from: http://www.centralbank.go.ke/index.php/interest-rates/time-series-data. Their frequency is monthly, and the sample goes from July 1991 to August 2010. The series are the commercial banks' weighted average interest rates for Deposit, Savings, Lending and Overdraft, and the 91-day Treasury bill rate. We will focus on the spreads in particular. As Treasury bills are generally considered risk-free (though as a result of the recent financial crisis this is now arguable), T-bill spreads can be seen as an indication of the perceived risk of default, whilst the spread between deposit and lending rates provides some information about banks' profit margins. On the other hand, the spread Lending – Saving may be considered as an approximate measure for the bank's interest margins. Finally, Deposits – Lending rate spreads are clearly related to the banking sector's ability to channel savings into productive uses.

**[Insert Figure 1 about here]**

We start by considering a model of the form given by equations (1) and (4) with $z_t = (1,t)^T$, i.e.,

$$y_t = \alpha + \beta t + x_t; \qquad (1-L)^d x_t = u_t, \quad t = 1, 2, \ldots, \qquad (5)$$

assuming first that the error term $u_t$ is white noise and then that it is autocorrelated. In the latter case, we assume that $u_t$ follows the exponential spectral model of Bloomfield (1973). This is a non-parametric approach that produces autocorrelations decaying exponentially as in the AR(MA) case. Its main advantage is that it mimics the behaviour of ARMA structures with a small number of parameters. Moreover, it is stationary independently of the values of its coefficients in contrast to the AR case.[6]

[6] See Gil-Alana (2004c) for the advantages of the model of Bloomfield (1973) in the context of Robinson's (1994) tests.

For each series, we consider the three standard cases examined in the literature, i.e., no regressors (i.e., $\alpha = \beta = 0$ a priori in (5)), an intercept ($\alpha$ unknown and $\beta = 0$ a priori), and an intercept with a linear time trend (i.e., $\alpha$ and $\beta$ unknown). Table 1 reports the (Whittle) estimates of *d* under the assumption of white noise errors. Table 2 refers to the model of Bloomfield (1973). In both cases we display along with the estimates the 95% interval of the non-rejection values of *d* using Robinson's (1994) parametric approach.

**[Insert Tables 1 and 2 about here]**

Starting with the results based on white noise disturbances, it can be seen that the estimates of *d* are above 1 in all cases, and the unit root null hypothesis is practically always rejected; the only exceptions, when the unit root cannot be rejected, are "*Savings*" and "*Overdraft*" if no deterministic terms are included in the model. Concerning the specification with an intercept (which is the most data congruent in view of the t-values of the time trend coefficients, not reported), the estimated values of d range between 1.147 (for "*Savings*") and 1.881 (for the "*91-day Treasury Bill rate*"). As for the case of autocorrelated (Bloomfield) errors (in Table 2), the results are fairly similar to those displayed in Table 1 with the exception of the "*Treasury Bill rate*". For this series, the estimated value of d is found to be below 1, although the unit root null cannot be rejected. For the remaining four series, the estimated value of d is strictly above 1 in all cases.[7]

[7] The results of several diagnostic tests on the residuals under the white noise specification support the hypothesis of autocorrelated errors. For the model of Bloomfield, we set q (the nuisance parameter) equal to 1, 2 and 3. Table 2 reports the results for $q = 1$. Very similar values were obtained with $q = 2$ and 3.

To corroborate the above results, we also implement a semiparametric approach to estimate d that is due to Robinson (1995). This is a "*local*" Whittle estimate in the frequency domain, based on a band of frequencies that degenerates to zero. It is implicitly defined by:

$$\hat{d} = arg\ min_{d} \left( log\ \overline{C(d)} - 2\ d\ \frac{1}{m} \sum_{j=1}^{m} log\ \lambda_j \right), \qquad (6)$$

$$for\ d \in (-1/2\ ,\ 1/2); \quad \overline{C(d)} = \frac{1}{m} \sum_{j=1}^{m} I(\lambda_j)\, \lambda_j^{2d}, \quad \lambda_j = \frac{2\,\pi\, j}{T}, \quad \frac{1}{m} + \frac{m}{T} \to 0,$$

where $T$ is the sample size, $m$ is the bandwidth parameter, and $I(\lambda_j)$ is the periodogram of the time series, $x_t$, given by:

$$I(\lambda_j) = \frac{1}{2\pi T} \left| \sum_{t=1}^{T} x_t\, e^{i \lambda_j t} \right|^2 .$$

Under finiteness of the fourth moment and other mild conditions, Robinson (1995) proved that:

$$\sqrt{m}\, (\hat{d} - d_o) \to_d N(0, 1/4) \quad as\ T \to \infty,$$

where $d_o$ is the true value of $d$ and with the only additional requirement that $m \to \infty$ slower than $T$.

**[Insert Figure 2 about here]**

The results based on the above approach are displayed in Figure 2. Given the nonstationary nature of the series examined, the values are estimated using first (second)- differenced data, then adding 1 (2)- to obtain the proper orders of integration of the series. It can be seen that the values are similar across the series. Along with the estimates we also present the 95% confidence interval of the non-rejection values corresponding to the *I(1)* hypothesis. We display the estimates for the whole range of values of the bandwidth parameter *m (= 1, 2, ...T/2).* It can be seen that, for small bandwidth parameters, some of the estimates are below 1 although still within the I(1) interval.[8]

**[Insert Table 3 about here]**

Table 3 displays the estimates of *d* for specific bandwidth parameters, in particular for *m* = 5, 10, 15 ( = $T^{0.5}$), 25, 50 and 100. The unit root null is rejected in the majority of cases in favour of higher orders of integration if the bandwidth parameter is equal to or higher than 25. However, for the more realistic cases of m = 10 or m = 15 (=$(T)^{0.5}$), the estimated values of d are now below 1 and mean reversion is found to be statistically significant for the Treasury Bill rate. Mean reversion has in fact rarely been discussed in the case of such "risk-free" assets, often being thought that it is a stock-only concept. One possible explanation for differences between Treasury bill and commercial rates is the different frequency of fiscal and monetary policy respectively (to which the latter rates are associated). For the remaining series, the fractional differencing parameter is found to be below 1, although the unit root null hypothesis cannot be rejected.

It could be argued that the finding of nonstationarity reported here reflects unaccounted breaks in the data. In fact, fractional integration and structural breaks are intimately related issues (Diebold and Inoue, 2001; Granger and Hyung, 2001). Visual inspection of the series in Figure 1 suggests that there might a break at the very beginning of the sample period. Thus, we obtained estimates of d for each series using different subsamples, in a recursive manner.

[8] When choosing the bandwidth there is a trade-off between bias and variance: the asymptotic variance is decreasing whilst the bias is increasing with *m*.

**[Insert Figure 3 about here]**

Figure 3 displays the estimates of *d* (and the 95% confidence intervals) with white noise disturbances, first for the whole sample and then removing one observation at a time from the beginning of the sample to the observation corresponding to December 1993. It can be seen that for Deposits, Savings and Lending the values of d are relatively stable; for Overdraft there is an increase from approximately 1.15 to 1.3 at the end of 1993, and finally, for the 91-Day Treasury Bill rate, a decrease of about 0.2, from 1.8 to 1.6, after removing the first two years of data. Very similar results (not reported) were obtained for the case of autocorrelated errors, the estimates for Deposits, Saving and Lending being very stable, whilst they are less so in the case of the other two series. Overall, the results confirm our hypothesis that the five series are nonstationary with orders of integration around 1. Therefore, the effects of shocks will either die out extremely slowly or even be permanent and thus decisive policy intervention will be necessary to bring interest rates back to their original levels as long as the shocks result from exchange rate changes, interest rate changes abroad etc. rather than policy measures of the national central bank itself. The high level of dependence observed in some of these series could be the result of an incorrect interest rate policy, implying the desirability of a policy aimed at reducing interest rate volatility. As already mentioned in the introduction, the stochastic properties of the commercial rates depend on the interest rates set by the central bank and how they are used to respond to shocks, and consequently both the stochastic properties of those and the adequacy of monetary policy will determine their path over time (whilst the Treasury bill rate is directly related to fiscal policy). In particular, the stochastic behaviour of spreads is informative about the (in)ability of the central bank to control commercial rates. It should be stressed that the nonstationary nature of the series implies that shocks will have permanent effects requiring policy action to bring the variables back to their pre-shock equilibrium values, but does not provide any information about the nature of the shocks, specifically whether they are real or monetary.

## 5. Analysing the spreads

In this section we focus on the spreads, and in particular we examine the following differences: Lending – 91 Day Treasury Bill rate; Lending – Saving rate; Deposit – 91 Day Treasury Bill rate, Saving – 91 Day Treasury Bill rate, and Deposits - Lending (see Figure 4).

**[Insert Figure 4 and Tables 4 and 5 about here]**

Tables 4 and 5 report the estimates for the two cases of white noise and autocorrelated (with Bloomfield) errors respectively. Starting with the case of uncorrelated errors (Table 4), it can be seen that the estimates of d are extremely large (around 1.8) for three of the spreads (Lending - Treasury Bill; Deposit - Treasury Bill; and Saving - Treasury Bill), and around 1 (with the unit root not being rejected at conventional statistical levels) for the Lending – Saving, and Deposits – Lending spreads. However, in the more realistic case of autocorrelated errors,[9] the values are much smaller; the unit root cannot be rejected for Lending – Treasury Bill, Lending – Saving, Saving – Treasury Bill and Deposits - Lending, and evidence of mean reversion (i.e., orders of integration strictly smaller than 1) is only found in the case of the Deposits – Treasury Bill rate spread.

[9] Several diagnostic tests for serial correlation conducted on the estimated residuals under the white Boise specification reject the null of no serial correlation in all cases examined.

The results for the spreads based on the semiparametric estimation method of Robinson (1995) are displayed in Figure 5. For the Lending –Saving and Deposits – Lending spreads, the estimates are within the I(1) interval; however, for the remaining three spreads (related with the 91 Day Treasury Bill rate) the values are significantly above 0 and below 1, implying long memory and mean-reverting behaviour. Table 6 shows the estimates for specific bandwidth parameters confirming that mean reversion takes place in the cases of the Lending – Treasure Bill rate, Deposits – Treasure Bill rate, and Saving – Treasure Bill rate, but not for the Lending – Saving and Deposits – Lending spreads. Taking into account the possible presence of outliers, specifically one at the beginning of the sample (see again Figure 4), did not affect the conclusions. Overall, the structure of interest rates in Kenya is found to display a high degree of persistence, implying the need for policy actions to make markets more flexible and competitive. This is in contrast to the evidence for Europe and other developed markets (see, e.g., Rose, 1988; Stock and Watson, 1988; Wu and Chen, 2001) which suggests that the standard parity conditions linking interest rates in the long run hold instead in these countries.

**[Insert Figure 5 and Table 6 about here]**

## 6. Conclusions

This paper has investigated the interest rate structure in Kenya using procedures based on long-range dependence. In particular, it has examined the orders of integrations of four commercial banks' interest rates (Deposits, Savings, Lending and Overdraft) along with the 91-Day Treasury Bill rate for the period July, 1991 – August, 2010. The results suggest that, regardless of the estimation method used, the T-Bill rate is likely to exhibit mean reversion, while evidence for mean reversion is weak for the commercial bank rates.

The evidence for the spreads is similar, mean reversion being found only in the case of the spreads vis-à-vis the 91 Day Treasure Bill rate under the assumption of autocorrelated errors. The implication of these results is that shocks to interest rates have permanent or long-lived effects and therefore decisive policy measures will need to be implemented to achieve mean reversion in interest rates.

It should be noted that the primary objective of the Central Bank of Kenya is price stability, and therefore fiscal and monetary policy have been independent over the sample span analysed. The focus of monetary authorities has been on maintaining high interest rates so as to reduce the inflation rate and also to avoid a significant depreciation of the Kenya shilling. This tight monetary policy stance is thought to reduce inflationary pressure and also to promote portfolio investment inflows into Kenya, thus improving the capital account. It could also have a detrimental effect on growth, but the findings in Caporale et al. (2012) suggest that a less contractionary monetary policy by the Central Bank of Kenya could be combined with an appropriate exchange rate policy (i.e., a moderate depreciation of the Kenyan shilling) to achieve more effectively the objectives of internal and external balance in Kenya.

The results reported here are in sharp contrast to what is typically observed in the case of the developed economies, where interest rates are generally found to be mean-reverting, at least when using the same *I(d)* techniques as those employed in this study. Since any breaks seem to occur at either end of the sample, formal tests for structural change cannot be carried out within an *I(d)* framework such as ours. Non-linear methods might be informative in this respect. Work in this direction is in progress.

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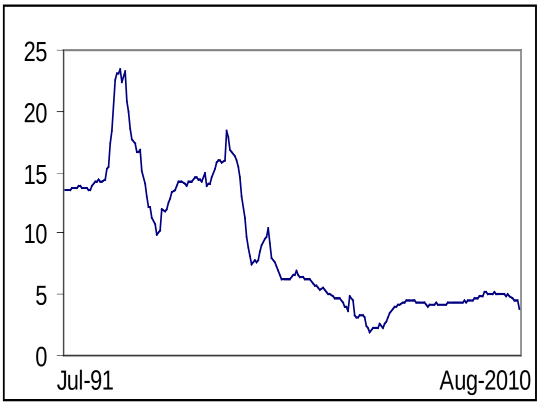
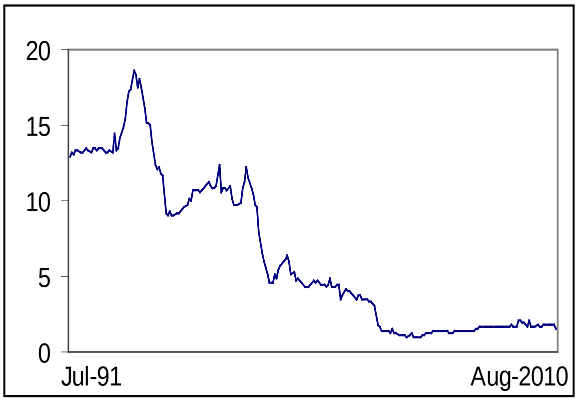
**Figure 1: Time series plots of the commercial bank's weighted average interest rates and the 91-day Treasury Bill rate**

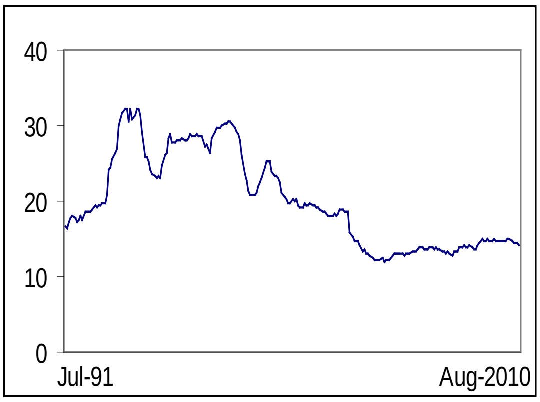
Deposit



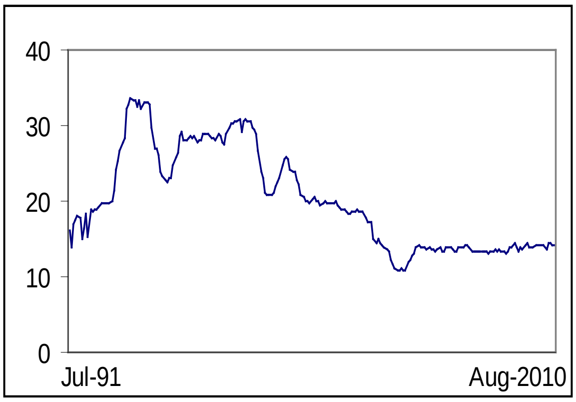

Savings




Lending




Overdraft




91-Day Treasury Bill rate

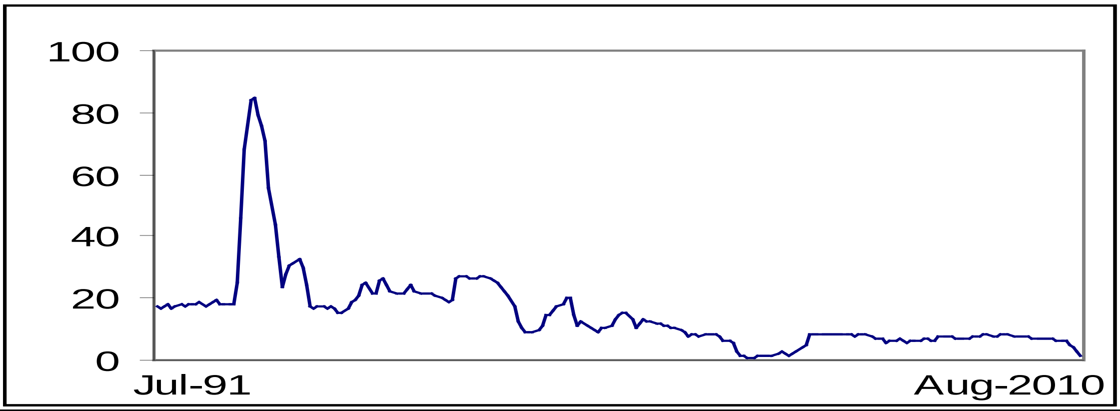
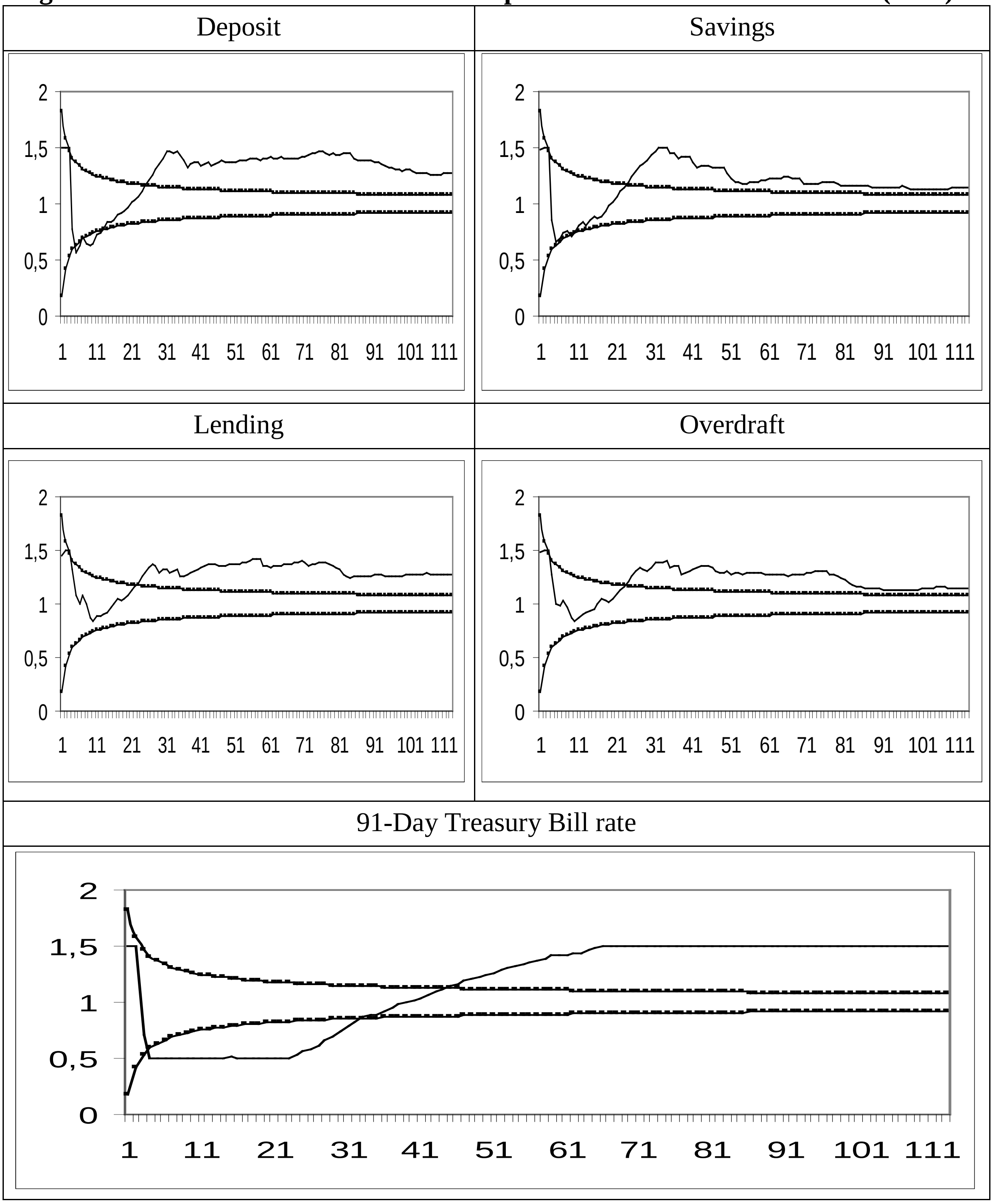
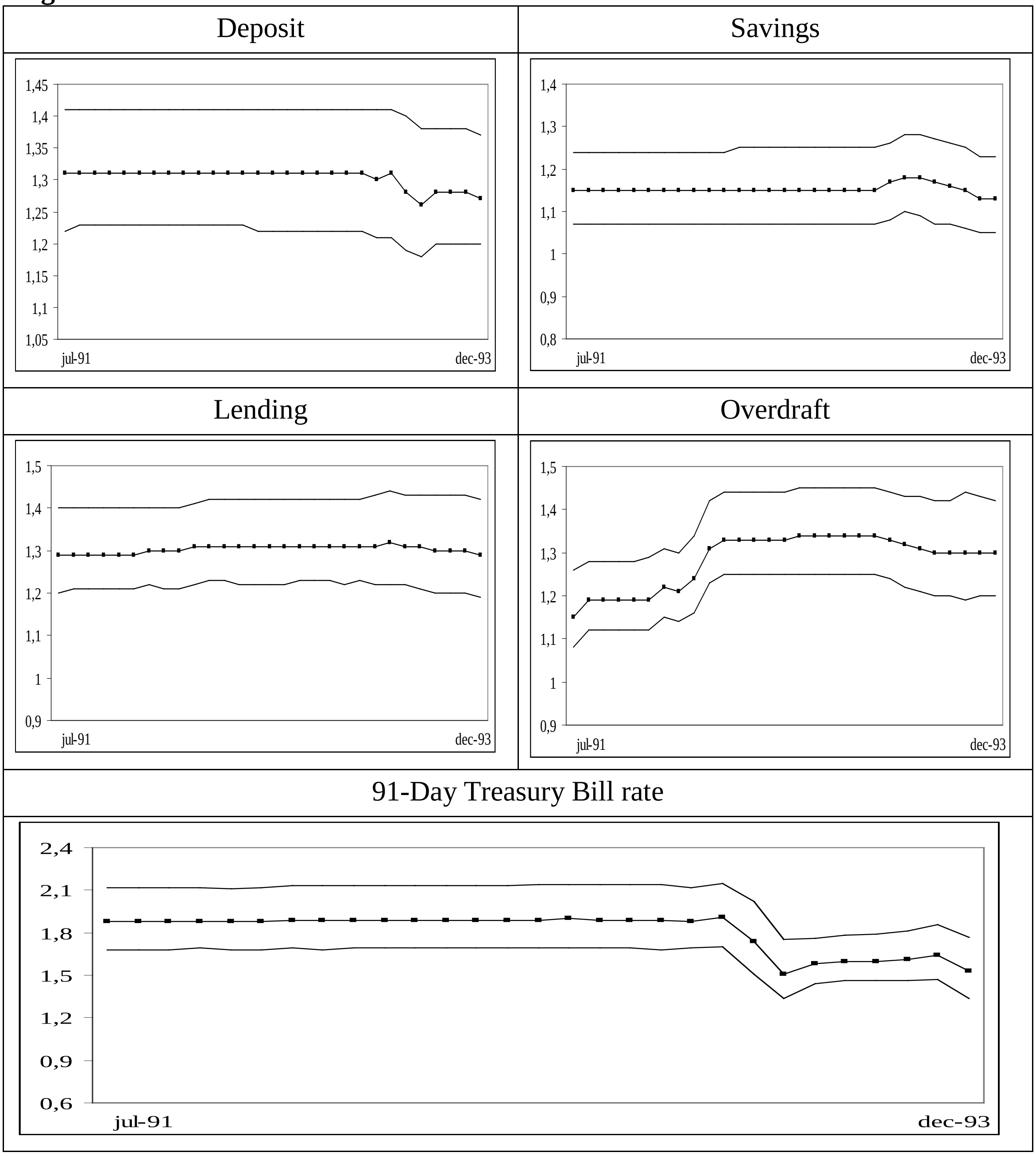


**Figure 2: Estimates of d based on the semiparametric method of Robinson (1995)**




The horizontal axis refers to the bandwidth parameter, while the vertical one reports the estimated value of d. The dotted lines represent the 95% confidence interval for the I(1) hypothesis.

**Figure 3: Recursive estimates of d**




The dotted line represent the estimated values of d, while the thin ones are the 95% confidence interval.

**Figure 4: Time series plots of the spreads**

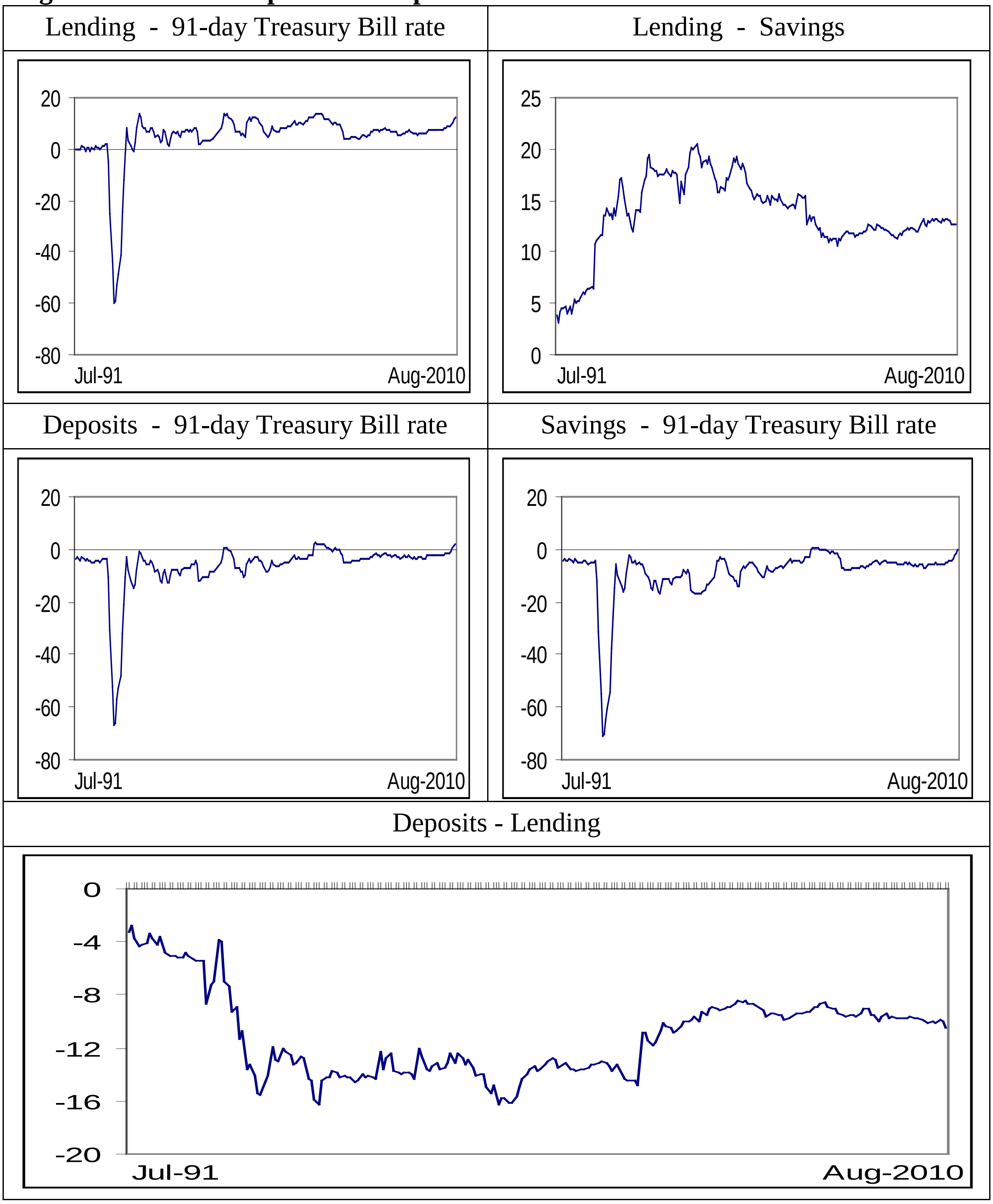
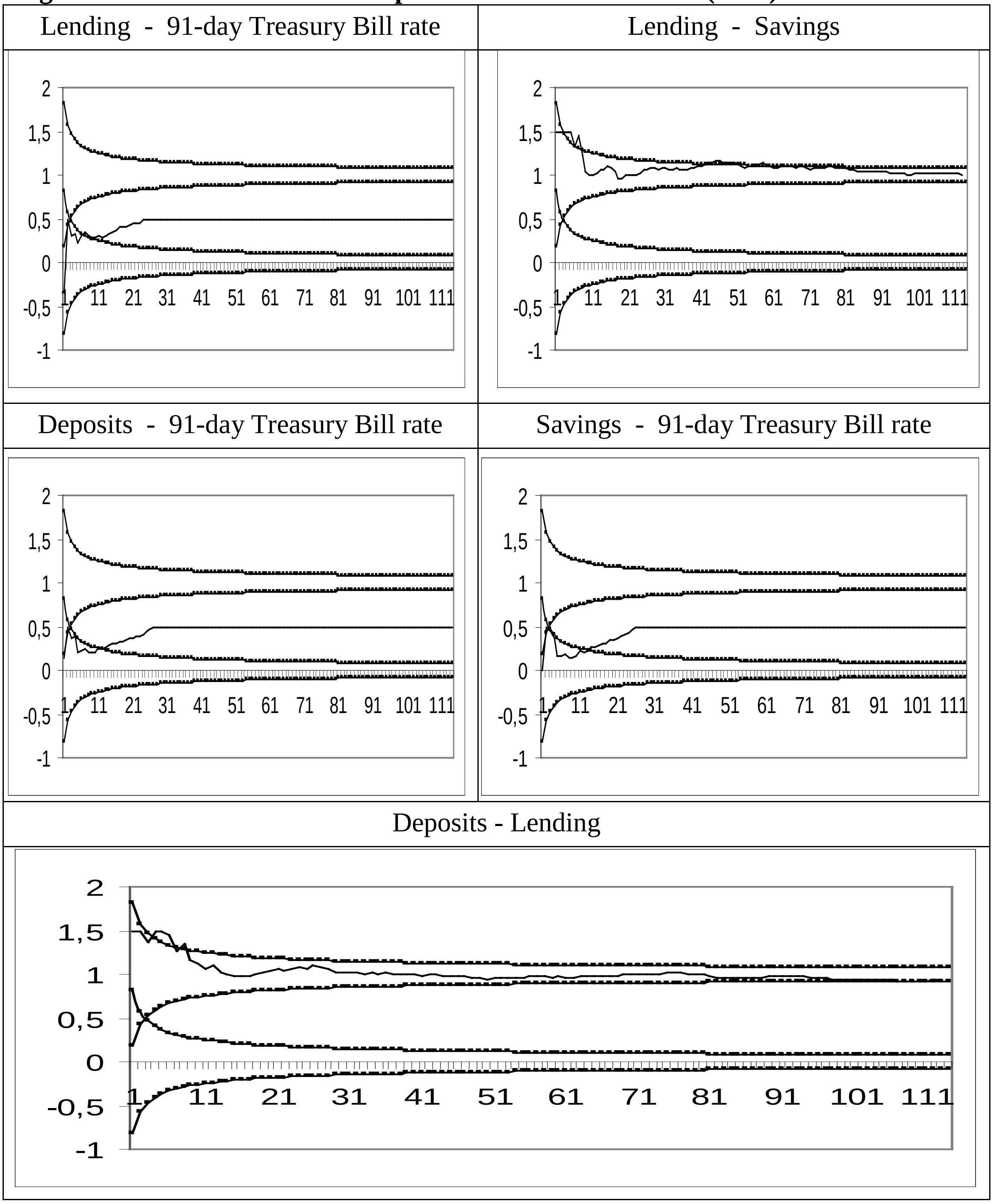


**Figure 5: Estimates of d for the spreads based on Robinson (1995)**




The horizontal axis refers to the bandwidth parameter, while the vertical one reports the estimated value of d. The dotted lines represent the 95% confidence interval for the I(0) and I(1) hypotheses.

**Table 1: Estimates of d based on Robinson (1994) using white noise disturbances**

| | No regressors | An intercept | A linear time trend |
|---|---|---|---|
| Deposits | 1.082<br>(1.007, 1.180) | 1.311<br>(1.224, 1.416) | 1.311<br>(1.224, 1.416) |
| Savings | 1.039<br>(0.967, 1.135) | 1.147<br>(1.069, 1.245) | 1.147<br>(1.069, 1.245) |
| Lending | 1.090<br>(1.019, 1.184) | 1.292<br>(1.207, 1.399) | 1.291<br>(1.206, 1.398) |
| Overdraft | 1.049<br>(0.988, 1.128) | 1.158<br>(1.084, 1.252) | 1.158<br>(1.084, 1.251) |
| 91-day Treasury Bill | 1.651<br>(1.482, 1.851) | 1.881<br>(1.679, 2.121) | 1.881<br>(1.679, 2.121) |

The reported values are Whittle estimates of d in the frequency domain. Those in parentheses are the 95% confidence intervals of non-rejection values of d using Robinson's (1994) tests.

**Table 2: Estimates of d based on Robinson (1994) using Bloomfield disturbances**

| | No regressors | An intercept | A linear time trend |
|---|---|---|---|
| Deposits | 1.110<br>(0.967, 1.308) | 1.429<br>(1.179, 1.750) | 1.429<br>(1.179, 1.751) |
| Savings | 1.039<br>(0.923, 1.231) | 1.228<br>(1.038, 1.501) | 1.228<br>(1.038, 1.501) |
| Lending | 1.138<br>(1.004, 1.337) | 1.308<br>(1.112, 1.588) | 1.322<br>(1.112, 1.587) |
| Overdraft | 1.260<br>(1.102, 1.530) | 1.308<br>(1.114, 1.570) | 1.308<br>(1.114, 1.568) |
| 90-day Treasury Bill | 0.909<br>(0.710, 1.242) | 0.759<br>(0.563, 1.101) | 0.751<br>(0.525, 1.101) |

The reported values are Whittle estimates of d in the frequency domain. Those in parentheses are the 95% confidence intervals of non-rejection values of d using Robinson's (1994) tests. Q = 1 in all cases.

**Table 3: Estimates of d based on Robinson (1995) for various bandwidth parameter values**

| | 5 | 10 | 15 = $T^{0.5}$ | 25 | 50 | 100 |
|---|---|---|---|---|---|---|
| Deposits | 0.560* | 0.651* | 0.833 | 1.156 | 1.369 | 1.302 |
| Savings | 0.657* | 0.741 | 0.889 | 1.241 | 1.268 | 1.129 |
| Lending | 1.084 | 0.842 | 0.966 | 1.294 | 1.365 | 1.268 |
| Overdraft | 1.004 | 0.834 | 0.951 | 1.251 | 1.300 | 1.136 |
| 91-day Treasury Bill | 0.500 | 0.500 | 0.513* | 0.560* | 1.237 | 1.129 |
| 95% I(1) Confidence Interval | (0.739, 1.367) | (0.739, 1.260) | (0.787, 1.212) | (0.835, 1.164) | (0.883, 1.116) | (0.917, 1.082) |

“ * “ indicates that the null hypothesis of a unit root cannot be rejected at the 5% level.

**Table 4: Estimates of d based on Robinson (1994) using white noise disturbances**

| | No regressors | An intercept | A linear time trend |
|---|---|---|---|
| Lending – 91 T Bill | 1.815<br>(1.628, 2.032) | 1.815<br>(1.629, 2.032) | 1.815<br>(1.629, 2.032) |
| Lending – Saving | 1.006<br>(0.943, 1.089) | 1.006<br>(0.941, 1.093) | 1.006<br>(0.943, 1.091) |
| Deposit – 91 T Bill | 1.815<br>(1.605, 2.066) | 1.833<br>(1.619, 2.088) | 1.833<br>(1.619, 2.088) |
| Saving – 91 T Bill | 1.832<br>(1.636, 2.063) | 1.855<br>(1.656, 2.092) | 1.856<br>(1.656, 2.092) |
| Deposits - Lending | 0.937<br>(0.875, 1.020) | 0.917<br>(0.853, 1.002) | 0.920<br>(0.859, 1.002) |

The reported values are Whittle estimates of d in the frequency domain. Those in parentheses refer to the 95% confidence intervals of the non-rejection values of d using Robinson's (1994) tests.

**Table 5: Estimates of d based on Robinson (1994) using Bloomfield disturbances**

| | No regressors | An intercept | A linear time trend |
|---|---|---|---|
| Lending – 91 T Bill | 0.793<br>(0.519, 1.175) | 0.794<br>(0.525, 1.176) | 0.786<br>(0.523, 1.176) |
| Lending – Saving | 1.113<br>(0.993, 1.324) | 1.108<br>(0.978, 1.308) | 1.098<br>(0.979, 1.297) |
| Deposit – 91 T Bill | 0.793<br>(0.519, 1.175) | 0.599<br>(0.371, 0.930) | 0.579<br>(0.327, 0.931) |
| Saving – 91 T Bill | 0.728<br>(0.511, 1.086) | 0.711<br>(0.456, 1.039) | 0.711<br>(0.452, 1.039) |
| Deposits - Lending | 1.027<br>(0.911, 1.182) | 0.994<br>(0.872, 1.157) | 0.994<br>(0.884, 1.146) |

The reported values are Whittle estimates of d in the frequency domain. Those in parentheses refer to the 95% confidence intervals of the non-rejection values of d using Robinson's (1994) tests. Q = 1 in all cases.

**Table 6: Estimates of d in the spreads based on Robinson (1995) for various bandwidth parameter values**

| | 5 | 10 | 15 = $T^{0.5}$ | 25 | 50 | 100 |
|---|---|---|---|---|---|---|
| Lending – 91 T Bill | 0.230* | 0.283* | 0.340* | 0.452* | 0.500 | 0.500 |
| Lending – Saving | 1.500 | 0.993 | 1.099 | 1.052 | 1.135 | 1.011 |
| Deposit – 91 T Bill | 0.198* | 0.213* | 0.298* | 0.442* | 0.500 | 0.500 |
| Saving – 91 T Bill | 0.157* | 0.162* | 0.272* | 0.465* | 0.500 | 0.500 |
| Deposits - Lending | 1.500 | 1.127 | 0.975 | 1.070 | 0.947 | 0.945 |
| 95% I(0) Confidence Interval | (-0.367, 0.367) | (-0.260, 0.260) | (-0.212, 0.212) | (-0.164, 0.164) | (-0.116, 0.116) | (-0.082, 0.082) |
| 95% I(1) Confidence Interval | (0.739, 1.367) | (0.739, 1.260) | (0.787, 1.212) | (0.835, 1.164) | (0.883, 1.116) | (0.917, 1.082) |

" * " indicates that the null hypothesis of a unit root is rejected at the 5% level.