

A Resolution of the Fisher Effect Puzzle: A Comparison of Estimators

Ekaterini Panopoulou*

National University of Ireland, Maynooth and University of Piraeus, Greece

May 2005

Abstract

This paper attempts a resolution of the Fisher effect puzzle in terms of estimator choice. Using both short-term and long-term interest rates for 14 OECD countries, we find ample evidence supporting the existence of a long-run Fisher effect in which interest rates move one-to-one with inflation. Our results suggest that the reason why the Fisher effect has not found support internationally lies on the estimation method. When the hypothesis of a unit coefficient relating interest rates to expected inflation is tested within the Autoregressive Distributed Lag (ADL) framework, which is invariant to the integration properties of the data, the Fisher effect easily survives the empirical evidence. Similar, but less robust, results are reached on the grounds of the Pre-Whitened Fully Modified Least Squares (PW-FMLS) or the Johansen's (JOH) estimators.

JEL Classification: E40; E50; C12; C13;

Keywords: Cointegration Estimators; Fisher Effect; ADL; DOLS; Small-sample properties

Word count: 5500

Acknowledgments: Financial support from the Greek Ministry of Education and the European Union under "Hrakteitos" grant is greatly appreciated. I am grateful to A. Antzoulatos, S. Kalyvitis, G.Hardouvelis, D. Malliaropoulos, M. Roche, M. Hurley, N.Pittis, D. Thomakos, E. Tzavalis and seminar participants at the 19th Irish Economic Association Annual Conference, IIIS Miniconference on International Financial Integration, National University of Ireland and the University of Peloponnesse for helpful suggestions and comments. The usual disclaimer applies.

* *Correspondence to:* Ekaterini Panopoulou, Department of Economics, National University of Ireland Maynooth, Co.Kildare, Republic of Ireland. E-mail: apano@nuim.ie. Tel: 00353 1 7083793. Fax: 00353 1 7083934.

1 Introduction

A vast literature is devoted to the size of the response of nominal interest rates to changes in expected inflation, broadly known as the Fisher effect.¹ The monetary neutrality implications for different Fisher effect values underlie this long-standing interest in the topic. More specifically, long-run superneutrality of money is associated with a coefficient relating interest rates to expected inflation equal to one, while a value below unity implies substantial long-run non-neutralities.

In this vein, the stationarity of the ex-ante real interest rate has some important implications. As suggested by the standard consumption asset pricing model, real interest rates should follow the pattern of consumption growth, which is clearly a stationary variable. Moreover, the neoclassical growth theory based on dynamic optimization for a representative economic agent implies that the real rate should be constant in the steady state, being proportional to the representative consumer's rate of time preference. Unfortunately there is no consensus among economists about the true size of the Fisher effect. There are several problems that plague empirical estimates of the Fisher effect. Darby (1975) introduced the effect of taxes on the size of the Fisher effect. He argued that nominal interest rates should increase by more than the increase in expected inflation to compensate debt holders for a lower after-tax return since interest income is usually taxed as ordinary income. In this case, we should obtain a Fisher effect estimate greater than one. A second problem is the generally unobserved nature of the expected inflation rate. When actual realized inflation is used to proxy expected inflation an errors-in-variables bias is introduced on the estimate of the Fisher effect. Another issue involves the time series properties of the data under consideration when estimating a relationship like the Fisher effect. The only case that standard least squares techniques are valid is when the series are second-order stationary. In the event of integrated variables, the only way to establish a theoretical Fisher relationship is via cointegration techniques.

Finally, even when applying the appropriate cointegration methods, severe problems

¹See e.g. Cooray, 2003 and the references therein.

may arise associated with the implementation of cointegration, such as the low power of cointegration tests or the performance of the various estimators in small samples. Crowder and Hoffman (1996) suggested that the estimator choice might account for the contradictory evidence in the literature. Specifically, the authors attribute the different conclusions reached in the literature regarding the relationship between inflation and interest rates to the differences in the small sample properties of the Ordinary Least Squares (OLS), the Dynamic Least Squares (DOLS) and the Johansen's (JOH) maximum likelihood estimators. More recently, Caporale and Pittis (2004) show that the estimators frequently employed in empirical studies, namely OLS and Fully Modified Least Squares (FMLS), are the ones with the least desirable small sample properties. The inability of these estimators to provide efficient estimates in small samples is likely to be responsible for the overrejection of the Fisher hypothesis. Specifically, the authors show that when the estimators with the best properties are chosen, the evidence is strongly supportive of the Fisher effect in the US.

In this study, we use both short-term and long-term interest rates and provide international evidence on a long-run Fisher effect, i.e. that interest rates and inflation move one-to-one in the long-run for 14 OECD countries. Using a variety of asymptotically efficient cointegration estimators we attempt to explain the Fisher effect puzzle in terms of estimator choice. We attribute the scarce evidence of an international Fisher effect in the literature to the poor small sample performance of the estimators employed so far. We particularly focus on two types of cointegration estimators that arise in the context of the Hendry-style Autoregressive Distributed Lag (ADL) models. The first type is usually referred to as the DOLS estimator (see Stock and Watson, 1993) and arises from a static cointegration equation augmented by current and past values of the first difference of the regressor. The second type, the ADL estimator (see Pesaran and Shin, 1999), is based on the projection of the cointegration error on the full information set, i.e. the current and past values of the first difference of the regressor plus the past values of the cointegration error. In an extensive Monte Carlo study, Panopoulou and Pittis (2004) highlighted the

potential pitfalls of employing the DOLS estimator as opposed to the ADL one in small samples for a wide variety of Data Generation Processes (DGPs). The authors showed that the ADL estimator, which utilizes the exact projection of the cointegration error on the full information set, offers a better framework for estimating the cointegration vector than the DOLS estimator that utilizes an approximate projection of the cointegration error on information provided only by the error that drives the regressor. To this end, the behavior of the ADL estimator seems to be the limiting one of the DOLS estimator. For comparison purposes, we also include some other commonly used cointegration estimators, such as the OLS and the semiparametric FMLS estimator of Phillips and Hansen (1990) and the Johansen's maximum likelihood estimator (1988, 1991).

The layout of this paper is as follows: Section 2 provides a brief literature review on the Fisher effect and a discussion of the Fisher equation. Section 3 outlines the econometric methodology used in the empirical analysis. Section 4 presents estimates of the Fisher equation obtained by the ADL and DOLS estimators for both our datasets, along with estimates obtained from the OLS, FMLS and JOH estimators. Section 5 summarizes the main findings of the paper.

2 Brief literature review

Ex ante real interest rates appear to be a key variable when investment - savings decisions and asset prices determination are considered. Their long-run behavior is often analyzed in the context of the Fisher (1930) relationship, linking nominal rates to expected inflation and requiring full adjustment of the former to the latter. The importance of this adjustment process stems from the fact that permanent shocks to either inflation or nominal rates should not be translated into permanent disturbances to real rates themselves, which would be problematic in the context of standard models of intertemporal asset pricing.

However, thus far the empirical evidence has not been supportive of the Fisher re-

relationship. Numerous studies have found that the slope coefficient in a regression of inflation against nominal rates is significantly different from one, at least over certain periods, (see e.g. Mishkin 1992 and Evans and Lewis, 1995).

Formally, the ‘Fisher effect’ can be expressed as:

$$i_t(m) = \pi_t^e(m) + r_t^e(m) \quad (1)$$

where $i_t(m)$ is the m -period nominal interest rate at time t , $\pi_t^e(m)$ denotes the expected rate of inflation from time t to $t+m$, and $r_t^e(m)$ is the ex-ante real interest rate. Assuming rational expectations (see, e.g. Mishkin, 1992), realized inflation is linked to expected inflation as follows:

$$\pi_t(m) = \pi_t^e(m) + e_t \quad (2)$$

where e_t is a white noise process, orthogonal to $\pi_t^e(m)$. If we further assume that the process followed by the real interest rate is a white noise process with a mean equal to r , we are able to test for the Fisher effect in the context of the following regression:

$$i_t(m) = r + \theta\pi_t(m) + \nu_t \quad (3)$$

The null hypothesis to be tested can take the form:

Fisher hypothesis holds \Leftrightarrow (i) ν_t is $I(0)$ and (ii) $\theta = 1$.

The first of these conditions, i.e. the condition that $i_t(m)$ and $\pi_t(m)$ are cointegrated processes is supported by the bulk of empirical evidence in the literature. On the other hand, when dealing with the second condition, estimates of θ appear to be significantly different from unity, leading to the Fisher effect puzzle.

Mishkin (1992) was one of the first to suggest that due to the apparent non-stationarity of nominal interest rates and inflation a possible source of the low Fisher effect estimates is the spurious regression problem discussed by Granger and Newbold (1974). He correctly pointed out that the Fisher relation should be treated within the context of a cointegrated

system, as in Engle and Granger (1987). Mishkin used the Engle-Granger OLS procedure to estimate the Fisher effect but did not derive any strong conclusions due to the large standard errors of the estimated parameters.

Subsequent studies used more efficient estimation procedures and generally found support for a long-run Fisher relation in the U.S. Evans and Lewis (1995) used the DOLS estimator and Crowder and Hoffman (1996) used the Johansen gaussian maximum likelihood estimator. Crowder and Hoffmann (1996) suggested that the estimator choice might account for the contradictory evidence gathered so far. In particular, the authors argue that differences in the small sample properties of the OLS, DOLS and JOH estimators are responsible for the vastly different conclusions reached in the literature about the relationship between inflation and interest rates. Their analysis, however, was much more limited than ours as they compared only three estimators in terms of small sample bias.

More recently, Atkins and Coe (2002) found evidence supporting the long-run Fisher effect for both Canada and the US using a variety of interest rates and the ARDL bounds test developed by Pesaran *et.al* (2001) which is capable of testing for the existence of a long-run relationship regardless of the integration properties of the underlying series. Fahmy and Kandil (2003) confirmed that inflation and interest rates exhibit common trends in the long-run and move in a one-to-one relation at long horizons, specifically when the assets' maturity exceeds two years. Their dataset includes, except for US, UK, Germany and Switzerland.

Caporale and Pittis (2004) employed virtually all available single-equation estimators and allowed for alternative data frequencies along with structural breaks.² The authors examined whether (i) differences in the estimate of θ from one can be attributed to small sample bias and (ii) rejections of the null reflect the use of asymptotic critical values rather than the empirical ones. They found evidence in favor of both claims, which implies that the Fisher hypothesis survives even when less satisfactory estimators are

²These cointegration estimators (most of which are asymptotically efficient) deal with the second order effects (long-run correlation and endogeneity effect) present in the OLS asymptotic distribution, either parametrically or non-parametrically.

employed provided that the empirical critical values are used. Choosing the estimator with the minimum bias and shift in the distribution of the associated t-statistics, valid inference can be conducted in support of the Fisher identity.

However, their study was confined to the US, which is the country usually employed in empirical studies on the Fisher hypothesis. There is some evidence, though, on the nominal interest rates and inflation relationship in other industrialized countries. Testing whether the Fisher relationship holds internationally is of interest since a necessary, but not sufficient, condition for real interest rates to be equalized internationally is that the Fisher relation holds in each country individually. Rose (1988) examined the integration properties of nominal interest rates and inflation for 18 OECD countries. He concluded that inflation does not appear to have a unit root, while nominal interest rates do. By contrast, Koustas and Serletis (1999) examined 10 industrialized countries and established that the conditions for meaningful Fisher effects, i.e. that inflation and interest rates are I(1) and cointegrated processes, hold. The authors, however, were not able to provide strong evidence in support of the Fisher hypothesis, i.e. to establish a unit coefficient.

3 Econometric Methodology

In this section, we consider two asymptotically efficient cointegration estimators on which our analysis is based, namely the ADL and DOLS estimators. The latter is a widely-used cointegration estimator suggested by Saikkonen (1991), Phillips and Loretan (1991) and Stock and Watson (1993), while the first developed by Pesaran and Shin (1999) is rarely employed in empirical applications despite its superiority in many aspects. Next, we show how these estimators are derived and compare their properties. We also briefly discuss the OLS, FMLS and JOH estimators. To facilitate the discussion, we employ the Phillips triangular representation of a cointegrated system.

Let \mathbf{z}_t and \mathbf{u}_t be two bivariate processes, with $\mathbf{z}_t = [y_t, x_t]^\top$ and $\mathbf{u}_t = [u_{1t}, u_{2t}]^\top$. We further assume that \mathbf{u}_t is a VAR(1) process, driven by $\mathbf{e}_t = [e_{1t}, e_{2t}]^\top$ and the generating

mechanism for y_t is given by the system

$$y_t = \theta x_t + u_{1t} \quad (4)$$

$$\Delta x_t = u_{2t} \quad (5)$$

$$\begin{pmatrix} u_{1t} \\ u_{2t} \end{pmatrix} = \begin{pmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{pmatrix} \begin{pmatrix} u_{1t-1} \\ u_{2t-1} \end{pmatrix} + \begin{pmatrix} e_{1t} \\ e_{2t} \end{pmatrix} \quad (6)$$

and

$$\begin{pmatrix} e_{1t} \\ e_{2t} \end{pmatrix} \sim NIID \left[\begin{pmatrix} 0 \\ 0 \end{pmatrix} \begin{pmatrix} \sigma_{11} & \sigma_{12} \\ \sigma_{12} & \sigma_{22} \end{pmatrix} \right] \quad (7)$$

for $t = 1, 2, \dots, T$.

Both eigenvalues of the matrix $A = [a_{ij}]$, $i, j = 1, 2$ are assumed to be less than one in modulus, in order for y_t and x_t to be I(1) variables, and the cointegration error to be an I(0) process. The long-run covariance matrix Ω and the one-sided covariance matrix Δ , needed to define the asymptotic nuisance parameters, are given by equations (8) and (9), respectively

$$\Omega = (I - A)^{-1} \Sigma (I - A^\top)^{-1} \quad (8)$$

$$\Delta = G(I - A^\top)^{-1} \quad (9)$$

where Σ denotes the innovations covariance matrix of the VAR and G is the unconditional covariance matrix of \mathbf{u}_t given by,

$$vecG = (I - A \otimes A)^{-1} vec\Sigma \quad (10)$$

An early result by Stock (1987) shows that the OLS estimator of θ obtained from (4) is super-consistent, regardless of the presence of temporal and/or contemporaneous correlation between the regression error, u_{1t} , and the error that drives the regressor, u_{2t} . On the other hand, in general, the asymptotic distribution of the OLS estimator of

θ falls outside the Local Asymptotic Mixture of Normals (LAMN) family and contains nuisance parameters. The reason for the presence of non-standard asymptotics is that in the presence of contemporaneous and temporal correlation between the elements of \mathbf{u}_t , two types of second-order asymptotic effects are present in the limiting distribution of the OLS estimator (see Phillips and Loretan 1991): The first is the nuisance parameter, ω_{12}/ω_{22} that describes the “long-run correlation” effect, due to non-diagonality of the long run covariance matrix $\Omega = [\omega_{ij}], i, j = 1, 2$. The second is the nuisance parameter $\delta_{21} = \sum_{k=0}^{\infty} E(u_{20}u_{1k})$ that describes the “endogeneity” effect.

In order to remove the second order effects parametrically, we must employ a new regression model whose error term is orthogonal to u_{2t} and u_{2t-i} , $i = 1, 2, \dots$. This can be done by employing the conditional expectation of u_{1t} either on the current and past values of u_{2t} or on the current and past values of u_{2t} plus the past values of u_{1t} . The first and second conditioning information sets result in the DOLS and ADL estimators, respectively. Next, we show how these estimators are actually derived, starting from the latter.

3.1 The ADL estimator

The full system (4) and (5) with errors specified by (6) - (7), implies the following conditional density of y_t :

$$D(y_t \mid x_t, \mathbf{z}_{t-1}^0, \lambda_1) = N(\theta_1 x_t + c_1 y_{t-1} + c_2 x_{t-1} + c_3 x_{t-2}, \sigma_v^2) \quad (11)$$

where $\lambda_1 \equiv (\theta_1, c_1, c_2, c_3, \sigma_v^2)$ and

$$\theta_1 = \theta + \frac{\sigma_{12}}{\sigma_{22}} \quad (12)$$

$$c_1 = a_{11} - a_{21} \frac{\sigma_{12}}{\sigma_{22}} \quad (13)$$

$$c_2 = a_{12} - \frac{\sigma_{12}}{\sigma_{22}} (a_{22} + 1 - a_{21}\theta) - a_{11}\theta \quad (14)$$

$$c_3 = (a_{22} \frac{\sigma_{12}}{\sigma_{22}} - a_{12}) \quad (15)$$

$$\sigma_\nu^2 = \sigma_{11} - \frac{\sigma_{12}^2}{\sigma_{22}} \quad (16)$$

This conditional model can be written as the ADL(q, r) regression, with orders $(q, r) = (1, 2)$:

$$y_t = \theta_1 x_t + c_1 y_{t-1} + c_2 x_{t-1} + c_3 x_{t-2} + \nu_t \quad (17)$$

The new error term, ν_t , is now orthogonal to $u_{2t}, \mathbf{u}_{t-1}, \mathbf{u}_{t-2}, \dots$ and its variance is given by (16).

In the context of the ADL(1,2) model the cointegration parameter θ is equal to the long-run multiplier of y_t with respect to x_t , that is

$$\theta = \frac{\theta_1 + c_2 + c_3}{1 - c_1} \quad (18)$$

We can estimate (17) by OLS and then use (18) to obtain an efficient estimate of θ . However, additional computations are required to obtain the variance of this estimate (see Banerjee *et. al.* 1993). A more convenient approach, proposed by Bewley (1979), transforms the model (17) in such a way that a point estimate of θ and its variance can be obtained directly. After some algebraic manipulation, model (17) can be equivalently written as:

$$y_t = \delta_0 \Delta y_t + \theta x_t + \lambda_0 \Delta x_t + \lambda_1 \Delta x_{t-1} + \eta_t \quad (19)$$

where

$$\delta_0 = -\frac{c_1}{(1-c_1)} \quad \lambda_0 = -\frac{c_2+c_3}{(1-c_1)} \quad \lambda_1 = -\frac{c_3}{(1-c_1)} \quad \eta_t = \frac{1}{(1-c_1)}\nu_t$$

Estimates of the coefficients and their standard errors can be obtained by using the Instrumental Variables (IV) estimator, with the original matrix of regressors, i.e. the variables in (17), being the instrumental variables (see Wickens and Breusch 1988). This means that the ADL estimator of θ is very easy to apply since it involves only IV estimation techniques.

3.2 The DOLS estimator

The ADL model, derived above, may be thought of as arising from projecting u_{1t} on the full information set $B = (u_{2t}, \mathbf{u}_{t-1}, \mathbf{u}_{t-2}, \dots)$, that is

$$E(u_{1t} | B) = \frac{\sigma_{12}}{\sigma_{22}} e_{2t} + a_{11} u_{1t-1} + a_{12} u_{2t-1} \quad (20)$$

As already mentioned, the second-order effects can be dealt with by projecting u_{1t} on a subset of this set, namely $A = (u_{2t}, u_{2t-1}, u_{2t-2}, \dots)$, $A \subset B$: The resulting conditional expectation involves an infinite sum,

$$E(u_{1t} | A) = \sum_{i=0}^{\infty} \beta_i u_{2t-i} \quad (21)$$

where β_i are functions of the parameters in (6)-(7). This conditional expectation does not admit a parsimonious representation analogous to (20). On the other hand, it allows for direct substitution of this expression into (4), thus yielding the following model

$$y_t = \theta x_t + \sum_{i=0}^{\infty} \beta_i \Delta x_{t-i} + v_t \quad (22)$$

where v_t is, in general, a serially correlated error term. In particular, v_t follows the AR(1) model

$$v_t = \gamma_2 v_{t-1} + \varepsilon_t \quad (23)$$

where γ_2 is the MA coefficient in the ARMA (2,1) representation of u_{2t} . Simple OLS applied to (22) yields the DOLS(p) estimator of Stock and Watson (1993), where p denotes the lag length of the first differences of the regressor added to (22). The serial correlation of v_t does not raise any serious problems in the estimation of θ , provided that a consistent estimator of the long-run variance of v_t is employed, such as the one proposed by Newey and West (1987). Alternatively, the application of Generalized Least Squares

(GLS) on (22), ensures valid asymptotic inferences on θ .³ In this case, the estimator in use is the DGLS(p) one.

In practice, however, the second term on the right-hand side of (22) has to be replaced by an approximation in which the infinite sum is truncated at $i = p$. The resulting model accommodates a truncation remainder that is likely to increase the bias of the DOLS(p) estimator of θ . This bias grows with the persistence of the cointegration error. Increasing the truncation point reduces the DOLS bias, but increases its variance. Moreover, estimating (22) by OLS is not feasible if p is too large compared to the sample size. Saikkonen (1991) specifies an upper bound for the rate at which p is allowed to increase with the sample size T , which is given by the condition $p^3/T \rightarrow 0$. Nevertheless, this condition cannot be used to define the optimal value of p for any given sample size.

On the contrary, the ADL estimator does not accommodate any truncation remainder and more importantly, yields consistent estimates of the long-run coefficients that are asymptotically normal irrespective of whether the underlying regressors are $I(1)$ or $I(0)$. Finally, it is easy to show that the only case that the ADL and DOLS estimators are equivalent is this of a non-autocorrelated error in (4), which is a highly unlikely case in the case of macroeconomic applications. Specifically, the cointegration error is usually found to exhibit a high degree of persistence.

3.3 Other Cointegration Estimators

The OLS estimator: This is the ordinary least square estimator applied to the static equation (4).

The Fully Modified Least Squares (FMLS) estimator: Phillips and Hansen (1990) employ semi-parametric corrections for the long run correlation and endogeneity effects, which fully modify the OLS estimator and its attendant standard error, thus obtaining the so-called Fully-Modified Least Squares (FMLS) estimation method. The FMLS estimator is based on consistent estimation of the matrices Ω and Δ , which in

³Note that in the case of a linear regression which involves an $I(1)$ strictly exogenous regressor, the OLS is asymptotically equivalent to the GLS estimator (see Kramer 1986, Park and Phillips 1988).

turn requires the selection of a kernel and the determination of the bandwidth. We employ the Quadratic Spectral kernel, since it is the best with respect to an asymptotic truncated mean square error criterion in the class of kernels that necessarily generate positive semi-definite estimators of the long-run variance covariance matrix in finite samples. The bandwidth parameter, S_T , has been selected by applying the Andrews (1991) data-dependent procedure. Specifically, the optimal bandwidth parameter S_T^+ for the Quadratic Spectral kernel is

$$S_T^+ = 1.3221[a(2)T]^{1/5}$$

where $a(2)$ is a function of the unknown spectral density matrix of u_t at frequency zero, its second generalized derivative and a 4×4 weighting matrix of known constants. This means that $a(2)$ and hence S_T^+ are also unknown in practice. Estimates of $a(2)$ may be obtained either by estimating simple parametric models, as suggested by Andrews (1991), or non-parametrically following Newey and West (1994). In our study, we determine the bandwidth by means of the Andrews (1991) data-dependent procedure. Moreover, the “prewhitened” version of FMLS which filters the error vector $\hat{\mathbf{u}}_t$ prior to estimating Ω and Δ is also employed (see Andrews and Monahan, 1990 and Christou and Pittis 2002, for a discussion on the performance of the various versions of the FMLS estimator).

The Johansen’s Maximum Likelihood (JOH) Estimator: Finally, apart from the single-equation estimators discussed above, we also consider the system-based maximum likelihood estimator of θ , suggested by Johansen (1988, 1991). The order of the JOH estimator corresponds to the lag-order of the Vector Autoregressive Model on which this estimator is based. This estimator differs from all the above mentioned estimators in an important respect: It has been developed and proved to be asymptotically optimal in the context of a Gaussian Vector Autoregression which accommodates a rather narrow class of DGPs.

4 Empirical Analysis

In this study we use both short-term and long-term nominal interest rates and inflation rates over the last fifty years collected from 14 OECD countries to examine whether the Fisher relation has empirical support internationally. Our main focus, however, is on the ability of the DOLS/DGLS estimators to provide valid inference as opposed to the ADL class of estimators. For comparison purposes, we also include the standard OLS estimator along with two versions of the Fully Modified Least Squares (FMLS) estimator and the Gaussian JOH estimator.

4.1 Data

The quarterly data on short-term interest rates (3-month T-bills) employed in this study were obtained from the OECD Main Economic Indicators and cover the period of 1960:1 to 2004:3. Annualised log changes in the consumer price level serve as a proxy for expected inflation. The annual data were taken from the International Financial Statistics of the IMF. They consist of annual observations on long-term nominal interest rates on government debt and consumer price inflation rates and cover the period from 1948 to 2003. The following nations are included: Australia, Belgium, Canada, France, Germany, Ireland, Italy, Netherlands, Norway, Portugal, Sweden, Switzerland, the United States and the United Kingdom.

4.2 Estimation Results

4.2.1 Quarterly data on short-term interest rates

Some preliminary results confirm the widely held view that interest rates and inflation rates are $I(1)$ processes and cointegrated.⁴ As a result, the first condition for the Fisher hypothesis to hold is satisfied. In this mode, we focus on testing the second hypothesis, namely that the slope coefficient is insignificantly different from one. In detail, we em-

⁴The results are not reported for brevity, but are available from the authors upon request.

ploy one version of the ADL estimator, the ADL(1,2) estimator. As regards the DOLS(p) estimator, we consider 20 estimators, by allowing the truncation parameter, p , to take values in the interval $[1, 20]$ by steps of 1. The serial correlation effect on the DOLS(p) estimator is taken into account by means of the autocorrelation consistent covariance matrix estimator of Newey and West (1987). The bandwidth parameter is estimated non-parametrically according to Newey and West (1994). We further assume an AR(1) model for the cointegration error and employ the feasible generalized least squares estimator. The resulting estimators are referred to as the DGLS(p). As mentioned in the introduction, the comparison is extended to include some other commonly used estimators, such as the OLS and the FMLS estimators. We consistently estimate the matrices Ω and Δ within the FMLS framework by employing the Quadratic Spectral kernel and determine the bandwidth by means of the Andrews (1991) data-dependent procedure. Moreover, the “prewhitened” version of FMLS (PW-FMLS) which filters the error vector $\hat{\mathbf{u}}_t$ prior to estimating Ω and Δ is also employed.

The estimates of θ are reported in the Appendix (Tables 1A-1E) along with the associated standard errors and the t-tests for the null hypothesis of interest $\theta = 1$ for all the countries under consideration. The main results are summarized in Table 1.

Table 1: Fisher effect estimates (Quarterly data)

Country	OLS	JOH	FMLS	PW-FMLS	ADL(1,2)	p_{DOLS}^*	p_{DGLS}^*
Australia	0.411	1.294*	0.499	0.891*	0.721*	13	>20
Belgium	0.433	1.351*	0.573	0.971*	0.722*	17	>20
Canada	0.598	1.195*	0.677	1.101*	0.959*	>20	>20
France	0.441	0.918*	0.438	0.627*	0.707*	>20	>20
Germany	0.444	1.575	0.526	1.339*	0.787*	2	7
Ireland	0.488	1.535*	0.749*	1.248*	1.278*	12	7
Italy	0.480	1.014*	0.594	0.772*	0.999*	>20	10
Netherlands	0.415	0.998*	0.524	0.806*	0.902*	>20	>20
Norway	0.547	1.425	0.795*	1.245*	1.135*	18	19
Portugal	0.517	1.254	0.716*	1.051*	1.107*	>20	7
Sweden	0.579	1.352	0.864*	1.259*	0.975*	4	10
Switzerland	0.596	1.344	0.776*	1.256*	0.860*	3	>20
UK	0.416	1.092*	0.583	0.926*	0.912*	>20	16
US	0.696	1.451	0.802*	1.218*	1.053*	16	18

Notes: The last two columns report the lag length p^* of the DOLS(p)/ DGLS(p) estimators necessary to approximate the ADL(1,2) coefficient estimate.

An asterisk denotes non-rejection of the null of a unit coefficient estimate ($H_0: \hat{\theta} = 1$).

Starting with the most commonly used estimator, the OLS estimator, we are able to reject the Fisher hypothesis in all countries. Specifically, the point estimates range from 0.411 (Australia) to 0.696 (US). The same holds when testing the Fisher hypothesis on the grounds of the DOLS(p)/DGLS(p) estimators for small values of p . Specifically, when $p \in [1, 2]$ the estimate of θ is significantly smaller than unity for all the countries under consideration. Thus, it appears that rejections of the Fisher hypothesis by means of the DOLS(p)/DGLS(p)-based t-statistics, as reported in Evans and Lewis (1995), may be solely attributed to an insufficiently large value of p .⁵ On the other hand, this hypothesis easily survives the empirical evidence if tested within the ADL(1,2) estimation framework. When the ADL(1,2) estimator is employed, the estimate of θ is insignificantly different from unity in all countries. The coefficient estimates increase substantially and range from 0.721 (Australia) to 1.278 (Ireland).

⁵The authors included 3 leads and lags of the first difference of the regressor in their model, which led to a coefficient value of 0.775, significantly different than unity.

We now move on to compare the ADL-type estimators to the DOLS-type estimators. As already mentioned, the ADL performance can be viewed as the limiting performance of the DOLS-type estimators. The last two columns of Table 1 report the lag length p of the DOLS(p)/DGLS(p) estimators necessary to approximate the coefficient value produced in the ADL(1,2) framework. When the DOLS(p) estimator is used, the lag length p^* necessary to reduce the bias of the DOLS estimator to the level of the ADL(1,2) ranges from 2 to over 20. In 11 out of 14 countries, the necessary lag length p exceeds 13, a value that is highly unlikely to be encountered in empirical applications. For example, Stock and Watson (1993), Muscatelli and Spinelli (2000) and Rapach and Wohar (2002) employ two lags and leads of the DOLS estimator. A similar picture emerges when the DGLS(p) estimator is considered with the lag length always exceeding 7. More importantly, however, the value of p that minimizes the bias of the DOLS(p)/DGLS(p) estimators is not the one that necessarily leads to a value of a t -statistic for testing the hypothesis of a unit coefficient in the Fisher relation similar to the one produced by the ADL estimator. For example, in the case of the DOLS(p) estimator for Australia, the lag length necessary for an equivalent bias between the ADL(1,2) and the DOLS(p) estimator is 13. In this case, however, the relevant t -statistics are -1.028 and -1.670 for the ADL(1,2) and the DOLS(7) estimators, respectively.

Turning to the FMLS estimators, we have to note that the performance of the FMLS resembles the one of the OLS and DOLS(p) estimator for small values of p , leading to a rejection of the null in 8 out of the 14 countries. This behavior of the FMLS estimator was documented in Panopoulou and Pittis (2004) through a Monte Carlo study for a variety of DGPs. In this study, the authors showed that significant gains can emerge when the “pre-whitened version” of the FMLS estimator is employed. This finding is confirmed in this study. We, specifically find that when employing the PW-FMLS the coefficient estimates increase substantially, leading to a non-rejection of the null in all the countries. From this point of view, the behavior of the PW-FMLS estimator seems to be similar to the ADL one.

Finally, when the JOH estimator is used, the Fisher hypothesis is rejected in approximately half the countries mainly due to increased coefficient estimates. In 10 out of 14 countries considered, the coefficient estimates exceed 1.20, a value consistent with a tax-effect as suggested by Darby (1975). Our estimate for the US of 1.199, insignificantly different from unity, is in line with the estimate of Crowder and Hoffman (1996) that find a coefficient of 1.22 for a similar dataset. However, Crowder and Hoffman (1996) conduct a Monte Carlo study and find that the 90% confidence interval for the bias of JOH is -0.04 to 0.16, while the respective figure for DOLS are -0.46 to -0.01. These intervals suggest that the estimates from DOLS exhibit downward bias, while the ones from JOH paint the opposite picture. Moreover, the extensive Monte Carlo study of Caporale and Pittis (2004) shows that the ADL(1,2) estimator exhibits minimal bias around -0.02, which further reinforces our preference for the ADL specification in this study.

Summing up, based on an ADL model, which has the additional advantage to be invariant of the integration properties of the variables, the Fisher effect is significant with a slope coefficient equal to unity in the 14 OECD countries under study. Next, we examine whether the same results hold in the case of long-term interest rates, specifically government bond yields.

4.2.2 Annual data on long-term interest rates

When the Fisher effect is tested with a different dataset including long-term as opposed to short-term interest rates, our results are qualitatively similar. The estimates of θ for this dataset are reported in the Appendix (Tables 2A-2E) along with the associated standard errors and the t-tests for the null hypothesis of interest $\theta = 1$ for all the countries under consideration. Moreover, the main results are summarized in Table 2.

Table 2: Fisher effect estimates (Annual data)

Country	OLS	JOH	FMLS	PW-FMLS	ADL(1,2)	p_{DOLS}^*	p_{DGLS}^*
Australia	0.251	1.561*	0.368	1.337*	1.166*	16	17
Belgium	0.450	1.779	0.714	1.007*	0.761*	5	7
Canada	0.574	1.068*	0.900*	1.234*	1.032*	13	13
France	0.334	1.185*	0.515	0.870*	0.767*	6	8
Germany	0.615	0.818*	1.136*	1.622	0.675*	7	8
Ireland	0.551	0.892*	0.833*	1.047*	0.686	3	5
Italy	0.539	0.879*	0.680	0.765	0.862*	11	8
Netherlands	0.238	0.992*	0.490	1.062*	0.665*	9	12
Norway	0.309	1.231*	0.464	1.490*	1.358*	13	19
Portugal	0.514	0.957*	0.605	0.752*	0.932*	>20	14
Sweden	0.470	1.308*	0.951*	1.275*	0.866*	2	7
Switzerland	0.356	0.843*	0.556	0.626	0.467	2	8
UK	0.526	1.015*	0.743*	0.986*	0.580	2	7
US	0.608	1.199*	1.020*	1.435*	1.126*	>20	10

Notes: See Table 1.

The Fisher hypothesis is rejected for all countries under consideration on the grounds of the OLS estimator with coefficient estimates ranging from 0.238 (Netherlands) to 0.615 (Germany). For a small value of p , for example $p \in [1, 2]$, the DOLS(p)/DGLS(p) estimators yield similar results leading to massive rejections of the null. On the other hand, when the ADL(1,2) estimator is employed, the estimate of θ is insignificantly different from unity in all countries but Ireland, Switzerland and UK. The coefficient estimates range from 0.467 (Switzerland) to 1.358 (Norway).

As previously, the last two columns of Table 2 report the lag length p of the DOLS(p)/DGLS(p) estimators necessary to approximate the coefficient value produced in the ADL(1,2) framework. Specifically, when the DOLS(p) estimator is used, the lag length p^* necessary to reduce the bias of the DOLS estimator to the level of the ADL(1,2) ranges from 2 to over 20. In 10 out of 14 countries, the necessary lag length p exceeds 5, a value rarely used in empirical applications. When the serial correlation in the error term is treated parametrically by employing the DGLS estimator, the necessary lag length always exceeds 5.

Turning to the FMLS estimators, we have to note that the employment of FMLS leads

to a rejection of the null in 8 out of the 14 countries. The possible downward bias of the FMLS estimator is sufficiently dealt with the prewhitening of the errors. The performance of PW-FMLS is sufficiently improved leading to a rejection of the null in only 20% of the countries. Interestingly, using either type of the FMLS estimator, we cannot reject the hypothesis of a unity coefficient for neither Ireland nor UK, a hypothesis rejected on the grounds of the ADL estimator. Specifically, the Ireland and the UK coefficient estimates are 1.047 and 0.980, for the PW-FMLS estimator.

Finally, the behavior of JOH is similar to the previous case suggesting coefficient estimates that exceed unity in half the countries considered. Despite this increase in estimates, the Fisher hypothesis is rejected only in the Belgium case.

5 Conclusions

We focused on the estimate of the coefficient linking nominal interest rates and inflation and the relevant hypothesis testing of a unit coefficient value in a sample of 14 OECD countries. Using both short-term and long-term interest rates, we found ample evidence supporting the Fisher hypothesis when this hypothesis is tested within the ADL framework or in the DOLS(p)/DGLS(p) framework with a sufficiently large value of p . In this context, we confirmed the superiority of the performance of the ADL-type estimators to that of the DOLS-type estimators using real data. Our study also included some other commonly used cointegration estimators, such as the OLS, FMLS and JOH estimators.

Our analysis shows that the reason why previous empirical studies have not found international empirical support for the Fisher hypothesis lies on the choice of the estimation method. The small sample properties of the cointegration estimators appear to be crucial when testing the Fisher hypothesis. As a result, when tested within the ADL framework, the Fisher effect easily survives the empirical evidence for the countries under consideration. In contrast, the employment of the DOLS(p)/DGLS(p) estimators, mainly employed in previous studies, produces massive rejections of the null, mainly due

to the insufficient inclusion of the lags of the first difference of the regressor. In some countries even 20 lags of the first difference of the regressor are not sufficient to bring the bias of the DOLS/DGLS estimators down to that of the ADL-type estimators. The performance of the OLS and FMLS estimator tends to imitate the one of the DOLS class of estimators, while significant gains emerge from the employment of the pre-whitened version of the FMLS estimator. This estimator performs almost as well as the ADL one. On the other hand, the performance of JOH is rather ambiguous and leads to mixed results. The estimates produced by this estimator are probably biased upwards leading to estimates that in many cases exceed unity significantly.

References

- [1] Andrews, D.W.K. (1991), Heteroskedasticity and Autocorrelation Consistent Covariance Matrix Estimation. *Econometrica*, 59, 817-858.
- [2] Andrews, D.W.K. and J.C. Monahan (1990), An improved heteroskedasticity and autocorrelation consistent covariance matrix estimator, *Yale Cowles Foundation D.P.* no. 942.
- [3] Atkins F. J. and P. J. Coe. (2002), An ARDL Bounds Test Approach to Testing the Long-run Fisher Effect in the United States and Canada, *Journal of Macroeconomics*, 24 (2), 255-266.
- [4] Banerjee, A., Dolado, J.J., Galbraith, J.W. and D.F. Hendry (1993), Cointegration, Error Correction and the Econometric Analysis of Non-Stationary Data, Oxford, Oxford University Press.
- [5] Barsky, R.B. (1987), The Fisher Hypothesis and the Forecastability and Persistence of Inflation, *Journal of Monetary Economics*, 19, 3-24.
- [6] Bewley, R.A (1979), The Direct Estimation of the Equilibrium Response in a Linear Model, *Economics Letters*, 3, 357-61
- [7] Caporale, G.M. and N. Pittis (2004), Estimator Choice and Fisher's Paradox: A Monte Carlo Study, *Econometric Reviews* , 23(1), 25-52.
- [8] Christou, C. and N. Pittis (2002), Kernel and Bandwidth Selection, Prewhitening, and the Performance of the Fully Modified Least Squares Estimation Method. *Econometric Theory*, 18, 948-961.
- [9] Cooray, A. (2003), The Fisher Effect: A survey. *The Singapore Economic Review*, 48(2), 135-150.
- [10] Crowder, W. and D. Hoffman (1996), The long-run relation between nominal interest rates and inflation: The Fisher equation revisited. *Journal of Money, Credit and Banking*, 28, 102-118.
- [11] Darby, M.R. (1975), The Financial and Tax effects of Monetary Policy on Interest Rates, *Economic Inquiry*, 13, 266-269.
- [12] Engle, R.F., D.F. Hendry and J.F. Richard (1983), Exogeneity, *Econometrica*, 51, 277-304.
- [13] Engle, R.F. and C.W.J Granger (1987), Cointegration and error correction representation, estimation and testing, *Econometrica*, 55, 251-276.
- [14] Evans M., K.Lewis (1995), Do expected shifts in inflation affect estimates of the long-run fisher relation? *Journal of Finance*, 50, 225-253.

- [15]Fahmy Y A. F. and M. Kandil (2003), The Fisher effect: new evidence and implications, *International Review of Economics & Finance*, 12, 4, 451-465.
- [16]Fisher, I. (1930), The theory of interest, Macmillan.
- [17]Granger, C.W.J and Newbold P. (1974), Spurious Regression in Econometrics, *Journal of Econometrics*, 2, 111-120.
- [18]Johansen, S. (1988), Statistical analysis of cointegrating vectors, *Journal of Economic Dynamics and Control*, 12, 231-254.
- [19]Johansen, S. (1991), Estimation and hypothesis testing of cointegration vectors in Gaussian vector autoregressive models, *Econometrica*, 59, 1551-1580.
- [20]Koustantas Z. and A. Serletis (1999), On the Fisher Effect. *Journal of Monetary Economics*, 44(1):105–30.
- [21]Kramer, W. (1986), Least-squares regression when the independent variable follows an ARIMA process, *Journal of the American Statistical Association*, 81, 150-154.
- [22]Mishkin, F.S.(1992), Is the Fisher effect for real? A reexamination of the relationship between inflation and interest rates. *Journal of Monetary Economics*, 30, 195-215.
- [23]Muscatelli V.A. and F. Spinelli (2000), The long-run stability of the demand for money: Italy 1861-1996. *Journal of Monetary Economics*, 45, 717-739.
- [24]Newey, W.K. and K.D. West (1987), A simple Positive, Semi-definite, Heteroskedasticity and Autocorrelation Consistent Covariance Matrix, *Econometrica*, 55, 703-708.
- [25]Newey, W.K. and K.D. West (1994), Automatic lag selection in covariance matrix estimation, *Review of Economic Studies*, 61, 4, 631-653.
- [26]Panopoulou E. and N. Pittis (2004), A comparison of autoregressive distributed lag and dynamic OLS cointegration estimators in the case of a serially correlated cointegration error, *The Econometrics Journal*, 7(2), 585-617.
- [27]Park, J.Y. and P.C.B. Phillips (1988), Statistical Inference in Regressions with Integrated Processes: Part 1, *Econometric Theory*, 4, 468-498.
- [28]Pesaran H.M. and Y. Shin (1999), An Autoregressive Distributed Lag Modelling Approach to Cointegration Analysis, *Econometrics and Economic Theory in the 20th Century: The Ragnar Frisch Centennial Symposium*, chapter 11. Cambridge University Press, Cambridge.
- [29]Pesaran H.M., Y. Shin and R.J. Smith (2001), Bounds testing approaches to the analysis of long-run relationships. *Journal of Applied Econometrics*, 16, 289-326.
- [30]Phillips, P.C.B. and E.J. Hansen (1990), Statistical inference in instrumental regressions with I(1) processes, *Review of Economic Studies*, 57, 99-125.
- [31]Phillips, P.C.B. and M. Loretan (1991), Estimating long-run economic equilibria, *Review of Economic Studies*, 58, 407-436.

- [32] Rapach, D.E. and M.E. Wohar (2002), Testing the monetary model of exchange rate determination: new evidence from a century of data, *Journal of International Economics*, 58(2), 359-385.
- [33] Rose, A.(1988) Is the Real Interest Rate Stable? *Journal of Finance*, 43(5):1095–1112.
- [34] Saikkonen, P. (1991), Asymptotically efficient estimation of the cointegrating regressions, *Econometric Theory*, 7,1, 1-27.
- [35] Stock, J.H. (1987), Asymptotic Properties of Least Squares Estimators of Cointegrating Vectors, *Econometrica*, 55, 1035-1056.
- [36] Stock, J.H. and M.W. Watson (1993), A simple estimator of cointegrating vectors in higher-order integrated systems, *Econometrica*, 61, 783-820.
- [37] Wickens, M.R. and T.S. Breusch (1988), Dynamic Specification, the Long Run and the Estimation of Transformed Regression Models, *Economic Journal*, 98, (Conference 1988), 189-205.

Appendix: Tables

Table 1A: Estimation Results – Quarterly short-term interest rates

Country	Australia			Belgium			Canada		
	$\hat{\theta}$	<i>s.e</i> ($\hat{\theta}$)	<i>t-test</i> $H_0: \hat{\theta}=1$	$\hat{\theta}$	<i>s.e</i> ($\hat{\theta}$)	<i>t-test</i> $H_0: \hat{\theta}=1$	$\hat{\theta}$	<i>s.e</i> ($\hat{\theta}$)	<i>t-test</i> $H_0: \hat{\theta}=1$
OLS	0.411	0.107	-5.537	0.433	0.116	-4.873	0.598	0.118	-3.415
ADL(1,2)	0.721	0.272	-1.028	0.722	0.414	-0.671	0.959	0.199	-0.202
JOH	1.294	0.241	1.218	1.351	0.312	1.124	1.195	0.151	1.291
FMLS	0.499	0.190	-2.628	0.573	0.194	-2.204	0.677	0.138	-2.334
PW-FMLS	0.891	0.204	-0.532	0.971	0.373	-0.079	1.101	0.188	0.535
DOLS 1	0.510	0.121	-4.069	0.509	0.152	-3.235	0.695	0.126	-2.417
DOLS 2	0.563	0.130	-3.360	0.540	0.170	-2.704	0.756	0.132	-1.853
DOLS 3	0.584	0.136	-3.053	0.551	0.183	-2.456	0.786	0.134	-1.592
DOLS 4	0.592	0.141	-2.903	0.548	0.189	-2.389	0.799	0.136	-1.481
DOLS 5	0.597	0.146	-2.770	0.549	0.193	-2.337	0.810	0.135	-1.408
DOLS 6	0.603	0.151	-2.639	0.555	0.190	-2.340	0.813	0.134	-1.391
DOLS 7	0.616	0.155	-2.485	0.570	0.183	-2.350	0.819	0.133	-1.360
DOLS 8	0.629	0.157	-2.365	0.590	0.173	-2.379	0.823	0.133	-1.329
DOLS 9	0.647	0.160	-2.212	0.608	0.166	-2.360	0.835	0.133	-1.235
DOLS 10	0.669	0.162	-2.047	0.620	0.169	-2.244	0.843	0.135	-1.164
DOLS 11	0.692	0.162	-1.897	0.622	0.177	-2.138	0.854	0.137	-1.071
DOLS 12	0.713	0.161	-1.784	0.615	0.185	-2.078	0.862	0.140	-0.991
DOLS 13	0.732	0.160	-1.670	0.617	0.196	-1.959	0.875	0.141	-0.887
DOLS 14	0.754	0.159	-1.546	0.636	0.203	-1.796	0.886	0.142	-0.804
DOLS 15	0.772	0.157	-1.446	0.659	0.211	-1.614	0.895	0.143	-0.734
DOLS 16	0.792	0.156	-1.337	0.687	0.219	-1.426	0.905	0.143	-0.668
DOLS 17	0.811	0.153	-1.233	0.732	0.224	-1.197	0.916	0.142	-0.594
DOLS 18	0.832	0.152	-1.106	0.776	0.225	-0.994	0.923	0.140	-0.554
DOLS 19	0.847	0.152	-1.008	0.813	0.224	-0.835	0.927	0.136	-0.542
DOLS 20	0.853	0.152	-0.968	0.853	0.218	-0.675	0.927	0.133	-0.549
DGLS 1	-0.021	0.055	-18.589	0.095	0.057	-15.950	0.116	0.050	-17.871
DGLS 2	0.153	0.084	-10.139	0.228	0.083	-9.290	0.253	0.074	-10.034
DGLS 3	0.289	0.114	-6.244	0.411	0.108	-5.470	0.406	0.104	-5.735
DGLS 4	0.368	0.132	-4.798	0.368	0.125	-5.075	0.505	0.124	-3.999
DGLS 5	0.364	0.149	-4.259	0.160	0.149	-5.658	0.643	0.137	-2.609
DGLS 6	0.299	0.164	-4.268	0.101	0.165	-5.464	0.581	0.155	-2.702
DGLS 7	0.267	0.182	-4.035	0.056	0.179	-5.277	0.634	0.168	-2.185
DGLS 8	0.184	0.200	-4.076	0.113	0.190	-4.661	0.609	0.179	-2.181
DGLS 9	0.050	0.223	-4.259	0.205	0.201	-3.965	0.706	0.183	-1.613
DGLS 10	0.072	0.240	-3.868	0.325	0.211	-3.198	0.657	0.194	-1.769
DGLS 11	0.195	0.247	-3.263	0.401	0.223	-2.683	0.671	0.203	-1.623
DGLS 12	0.270	0.254	-2.876	0.320	0.233	-2.921	0.609	0.217	-1.807
DGLS 13	0.186	0.275	-2.962	0.179	0.240	-3.417	0.641	0.220	-1.628
DGLS 14	0.376	0.264	-2.361	0.126	0.251	-3.488	0.686	0.227	-1.383
DGLS 15	0.395	0.270	-2.238	0.006	0.267	-3.717	0.629	0.244	-1.520
DGLS 16	0.361	0.285	-2.242	-0.161	0.281	-4.128	0.640	0.254	-1.421
DGLS 17	0.366	0.294	-2.157	-0.255	0.301	-4.170	0.769	0.241	-0.961
DGLS 18	0.498	0.284	-1.772	-0.145	0.319	-3.584	0.837	0.239	-0.683
DGLS 19	0.612	0.278	-1.396	-0.271	0.347	-3.664	0.857	0.244	-0.586
DGLS 20	0.468	0.311	-1.710	-0.169	0.373	-3.135	0.783	0.262	-0.828

Notes

1. The Newey and West (1987) method is employed in the DOLS(p) estimator.
2. An AR(1) model is assumed for the errors in the DGLS(p) estimator.

Table 1B: Estimation Results – Quarterly short-term interest rates

<i>Country</i>	<i>France</i>			<i>Germany</i>			<i>Ireland</i>		
	$\hat{\theta}$	<i>s.e.</i> ($\hat{\theta}$)	<i>t-test</i> $H_0: \hat{\theta}=1$	$\hat{\theta}$	<i>s.e.</i> ($\hat{\theta}$)	<i>t-test</i> $H_0: \hat{\theta}=1$	$\hat{\theta}$	<i>s.e.</i> ($\hat{\theta}$)	<i>t-test</i> $H_0: \hat{\theta}=1$
OLS	0.441	0.09	-6.185	0.444	0.095	-5.832	0.488	0.201	-2.544
ADL(1,2)	0.707	0.234	-1.249	0.787	0.366	-0.579	1.278	0.668	0.416
JOH	0.918	0.187	-0.440	1.575	0.157	3.671	1.535	0.854	0.626
FMLS	0.438	0.130	-4.336	0.526	0.157	-3.021	0.749	0.403	-0.621
PW-FMLS	0.627	0.228	-1.637	1.339	0.178	1.910	1.248	0.525	0.471
DOLS 1	0.475	0.094	-5.591	0.631	0.123	-2.995	0.687	0.260	-1.203
DOLS 2	0.492	0.098	-5.168	0.881	0.148	-0.805	0.820	0.269	-0.668
DOLS 3	0.500	0.104	-4.833	0.982	0.163	-0.109	0.840	0.312	-0.511
DOLS 4	0.499	0.110	-4.547	0.968	0.169	-0.192	0.773	0.330	-0.688
DOLS 5	0.505	0.116	-4.284	0.938	0.174	-0.355	0.795	0.310	-0.662
DOLS 6	0.507	0.120	-4.106	0.907	0.176	-0.528	0.814	0.307	-0.604
DOLS 7	0.512	0.122	-3.991	0.876	0.179	-0.693	0.816	0.314	-0.584
DOLS 8	0.521	0.123	-3.900	0.831	0.179	-0.948	0.904	0.307	-0.312
DOLS 9	0.530	0.122	-3.840	0.786	0.183	-1.169	1.047	0.320	0.148
DOLS 10	0.538	0.122	-3.780	0.749	0.191	-1.313	1.188	0.305	0.616
DOLS 11	0.547	0.123	-3.679	0.719	0.196	-1.430	1.237	0.305	0.777
DOLS 12	0.552	0.125	-3.590	0.669	0.193	-1.714	1.248	0.312	0.795
DOLS 13	0.551	0.125	-3.587	0.634	0.192	-1.910	1.318	0.302	1.054
DOLS 14	0.551	0.126	-3.581	0.617	0.195	-1.969	1.315	0.310	1.016
DOLS 15	0.556	0.128	-3.471	0.609	0.197	-1.987	1.294	0.315	0.932
DOLS 16	0.561	0.133	-3.307	0.579	0.198	-2.127	1.347	0.331	1.049
DOLS 17	0.563	0.139	-3.156	0.554	0.205	-2.181	1.358	0.313	1.142
DOLS 18	0.567	0.143	-3.035	0.529	0.213	-2.210	1.400	0.299	1.337
DOLS 19	0.577	0.145	-2.912	0.522	0.224	-2.135	1.498	0.283	1.760
DOLS 20	0.588	0.146	-2.824	0.504	0.231	-2.151	1.589	0.297	1.984
DGLS 1	0.272	0.073	-10.039	-0.045	0.042	-24.719	-0.167	0.263	-4.440
DGLS 2	0.410	0.096	-6.166	-0.057	0.078	-13.505	-0.307	0.429	-3.046
DGLS 3	0.584	0.114	-3.637	0.586	0.139	-2.980	0.865	0.577	-0.233
DGLS 4	0.501	0.128	-3.903	0.758	0.170	-1.422	1.112	0.577	0.195
DGLS 5	0.548	0.143	-3.165	0.772	0.195	-1.172	1.205	0.576	0.357
DGLS 6	0.503	0.155	-3.205	0.766	0.212	-1.103	1.208	0.579	0.360
DGLS 7	0.458	0.168	-3.232	0.867	0.230	-0.578	1.717	0.740	0.969
DGLS 8	0.477	0.175	-2.987	0.796	0.241	-0.849	1.673	0.714	0.942
DGLS 9	0.500	0.180	-2.784	0.716	0.244	-1.168	1.662	0.709	0.933
DGLS 10	0.476	0.189	-2.780	0.667	0.251	-1.328	1.664	0.689	0.964
DGLS 11	0.550	0.190	-2.369	0.753	0.261	-0.948	1.728	0.702	1.037
DGLS 12	0.637	0.195	-1.862	0.622	0.255	-1.482	1.676	0.746	0.905
DGLS 13	0.624	0.201	-1.871	0.541	0.252	-1.820	1.804	0.803	1.001
DGLS 14	0.565	0.210	-2.073	0.491	0.260	-1.957	1.913	0.849	1.075
DGLS 15	0.588	0.215	-1.916	0.520	0.267	-1.800	1.687	0.960	0.716
DGLS 16	0.609	0.218	-1.794	0.500	0.283	-1.766	1.985	1.014	0.971
DGLS 17	0.580	0.226	-1.857	0.475	0.294	-1.787	2.115	1.096	1.017
DGLS 18	0.550	0.237	-1.900	0.419	0.308	-1.885	2.431	1.227	1.166
DGLS 19	0.525	0.247	-1.922	0.440	0.322	-1.742	2.506	1.298	1.161
DGLS 20	0.480	0.263	-1.980	0.417	0.334	-1.746	2.441	1.200	1.201

Notes

1. The Newey and West (1987) method is employed in the DOLS(p) estimator.
2. An AR(1) model is assumed for the errors in the DGLS(p) estimator.

Table 1C: Estimation Results – Quarterly short-term interest rates

<i>Country</i>	<i>Italy</i>			<i>Netherlands</i>			<i>Norway</i>		
	$\hat{\theta}$	<i>s.e</i> ($\hat{\theta}$)	<i>t-test</i> <i>Ho: $\hat{\theta}=1$</i>	$\hat{\theta}$	<i>s.e</i> ($\hat{\theta}$)	<i>t-test</i> <i>Ho: $\hat{\theta}=1$</i>	$\hat{\theta}$	<i>s.e</i> ($\hat{\theta}$)	<i>t-test</i> <i>Ho: $\hat{\theta}=1$</i>
OLS	0.480	0.122	-4.252	0.415	0.084	-6.964	0.547	0.106	-4.255
ADL(1,2)	0.999	0.239	-0.003	0.902	0.209	-0.469	1.135	0.573	0.235
JOH	1.014	0.164	0.088	0.998	0.190	-0.009	1.425	0.196	2.164
FMLS	0.594	0.108	-3.758	0.524	0.140	-3.405	0.795	0.177	-1.155
PW-FMLS	0.772	0.182	-1.250	0.806	0.192	-1.006	1.245	0.220	1.105
DOLS 1	0.532	0.119	-3.937	0.505	0.099	-5.027	0.712	0.143	-2.012
DOLS 2	0.568	0.113	-3.820	0.546	0.109	-4.174	0.799	0.164	-1.226
DOLS 3	0.595	0.101	-4.011	0.566	0.114	-3.827	0.855	0.173	-0.844
DOLS 4	0.615	0.091	-4.231	0.579	0.114	-3.676	0.876	0.171	-0.724
DOLS 5	0.634	0.081	-4.497	0.587	0.112	-3.689	0.911	0.162	-0.550
DOLS 6	0.645	0.075	-4.706	0.598	0.108	-3.713	0.963	0.148	-0.249
DOLS 7	0.657	0.070	-4.885	0.610	0.105	-3.722	0.999	0.134	-0.010
DOLS 8	0.659	0.070	-4.842	0.620	0.101	-3.747	1.014	0.125	0.115
DOLS 9	0.662	0.073	-4.644	0.629	0.098	-3.776	1.035	0.123	0.282
DOLS 10	0.659	0.075	-4.557	0.642	0.096	-3.737	1.056	0.124	0.451
DOLS 11	0.657	0.076	-4.499	0.659	0.094	-3.625	1.068	0.125	0.544
DOLS 12	0.659	0.076	-4.512	0.673	0.092	-3.542	1.071	0.126	0.562
DOLS 13	0.664	0.075	-4.490	0.689	0.092	-3.404	1.077	0.124	0.619
DOLS 14	0.673	0.074	-4.414	0.708	0.092	-3.186	1.094	0.118	0.790
DOLS 15	0.677	0.074	-4.343	0.729	0.093	-2.924	1.111	0.112	0.990
DOLS 16	0.676	0.076	-4.276	0.740	0.093	-2.779	1.115	0.109	1.055
DOLS 17	0.673	0.076	-4.313	0.748	0.095	-2.653	1.121	0.106	1.141
DOLS 18	0.671	0.077	-4.271	0.755	0.097	-2.533	1.129	0.102	1.270
DOLS 19	0.669	0.079	-4.187	0.764	0.098	-2.407	1.142	0.098	1.450
DOLS 20	0.673	0.079	-4.149	0.774	0.098	-2.301	1.148	0.097	1.522
DGLS 1	0.161	0.059	-14.144	0.174	0.045	-18.455	-0.014	0.045	-22.728
DGLS 2	0.235	0.101	-7.577	0.360	0.055	-11.606	-0.014	0.069	-14.757
DGLS 3	0.445	0.135	-4.105	0.423	0.070	-8.289	0.017	0.108	-9.076
DGLS 4	0.577	0.151	-2.812	0.511	0.082	-5.938	-0.074	0.130	-8.248
DGLS 5	0.666	0.154	-2.170	0.471	0.099	-5.357	-0.172	0.150	-7.816
DGLS 6	0.663	0.165	-2.043	0.458	0.113	-4.785	-0.164	0.175	-6.646
DGLS 7	0.791	0.180	-1.164	0.508	0.126	-3.903	0.076	0.201	-4.601
DGLS 8	0.853	0.179	-0.821	0.536	0.139	-3.327	0.165	0.218	-3.836
DGLS 9	0.949	0.199	-0.259	0.450	0.153	-3.603	0.214	0.239	-3.292
DGLS 10	1.094	0.225	0.418	0.365	0.170	-3.729	0.265	0.263	-2.793
DGLS 11	1.054	0.238	0.227	0.463	0.176	-3.048	0.517	0.294	-1.644
DGLS 12	0.958	0.223	-0.189	0.433	0.187	-3.041	0.310	0.315	-2.189
DGLS 13	0.931	0.224	-0.310	0.382	0.200	-3.086	-0.039	0.320	-3.252
DGLS 14	0.942	0.239	-0.243	0.429	0.206	-2.773	-0.145	0.343	-3.335
DGLS 15	0.951	0.243	-0.204	0.636	0.198	-1.833	-0.094	0.389	-2.811
DGLS 16	0.966	0.228	-0.148	0.794	0.206	-0.999	-0.160	0.416	-2.791
DGLS 17	0.965	0.232	-0.150	0.808	0.218	-0.884	-0.221	0.447	-2.732
DGLS 18	0.955	0.250	-0.179	0.764	0.226	-1.044	-0.394	0.480	-2.906
DGLS 19	0.956	0.264	-0.168	0.791	0.235	-0.891	1.176	0.232	0.760
DGLS 20	0.995	0.297	-0.016	0.776	0.244	-0.921	1.222	0.227	0.976

Notes

1. The Newey and West (1987) method is employed in the DOLS(p) estimator.
2. An AR(1) model is assumed for the errors in the DGLS(p) estimator.

Table 1D: Estimation Results – Quarterly short-term interest rates

<i>Country</i>	<i>Portugal</i>			<i>Sweden</i>			<i>Switzerland</i>		
	$\hat{\theta}$	<i>s.e</i> ($\hat{\theta}$)	<i>t-test</i> $H_0: \hat{\theta}=1$	$\hat{\theta}$	<i>s.e</i> ($\hat{\theta}$)	<i>t-test</i> $H_0: \hat{\theta}=1$	$\hat{\theta}$	<i>s.e</i> ($\hat{\theta}$)	<i>t-test</i> $H_0: \hat{\theta}=1$
OLS	0.517	0.114	-4.255	0.579	0.077	-5.466	0.596	0.089	-4.501
ADL(1,2)	1.107	0.258	0.416	0.975	0.399	-0.063	0.860	0.209	-0.669
JOH	1.254	0.129	1.976	1.352	0.147	2.394	1.344	0.125	2.758
FMLS	0.716	0.157	-1.802	0.864	0.156	-0.867	0.776	0.149	-1.503
PW-FMLS	1.051	0.187	0.273	1.259	0.188	1.378	1.256	0.169	1.516
DOLS 1	0.651	0.124	-2.808	0.772	0.094	-2.437	0.742	0.100	-2.573
DOLS 2	0.866	0.119	-1.125	0.891	0.099	-1.095	0.858	0.105	-1.349
DOLS 3	0.906	0.099	-0.946	0.970	0.100	-0.303	0.913	0.118	-0.737
DOLS 4	0.921	0.090	-0.880	0.992	0.100	-0.077	0.915	0.121	-0.702
DOLS 5	0.914	0.091	-0.941	1.009	0.098	0.094	0.906	0.124	-0.762
DOLS 6	0.913	0.093	-0.943	1.042	0.092	0.457	0.892	0.128	-0.840
DOLS 7	0.913	0.094	-0.927	1.070	0.091	0.777	0.880	0.136	-0.887
DOLS 8	0.927	0.094	-0.785	1.071	0.092	0.771	0.874	0.139	-0.910
DOLS 9	0.935	0.094	-0.694	1.072	0.093	0.775	0.874	0.141	-0.897
DOLS 10	0.934	0.095	-0.701	1.075	0.096	0.783	0.884	0.137	-0.850
DOLS 11	0.933	0.096	-0.697	1.077	0.097	0.794	0.876	0.133	-0.934
DOLS 12	0.934	0.098	-0.671	1.078	0.099	0.784	0.848	0.130	-1.170
DOLS 13	0.944	0.098	-0.569	1.078	0.101	0.778	0.820	0.130	-1.388
DOLS 14	0.950	0.098	-0.508	1.083	0.102	0.809	0.807	0.132	-1.471
DOLS 15	0.947	0.101	-0.531	1.093	0.102	0.909	0.791	0.134	-1.554
DOLS 16	0.942	0.106	-0.553	1.103	0.100	1.026	0.788	0.141	-1.503
DOLS 17	0.947	0.109	-0.493	1.114	0.096	1.191	0.774	0.154	-1.467
DOLS 18	0.962	0.110	-0.344	1.124	0.091	1.371	0.759	0.170	-1.414
DOLS 19	0.981	0.110	-0.168	1.131	0.088	1.491	0.742	0.185	-1.396
DOLS 20	0.992	0.110	-0.074	1.143	0.083	1.719	0.737	0.197	-1.336
DGLS 1	-0.032	0.043	-23.845	-0.026	0.048	-21.275	0.075	0.048	-19.282
DGLS 2	-0.065	0.088	-12.078	-0.116	0.077	-14.520	0.020	0.078	-12.616
DGLS 3	0.093	0.159	-5.707	0.013	0.121	-8.185	0.383	0.120	-5.142
DGLS 4	0.352	0.188	-3.442	0.045	0.149	-6.431	0.624	0.145	-2.594
DGLS 5	0.460	0.199	-2.718	-0.127	0.164	-6.886	0.659	0.169	-2.020
DGLS 6	1.054	0.125	0.431	-0.018	0.185	-5.509	0.647	0.185	-1.908
DGLS 7	1.101	0.134	0.749	0.275	0.218	-3.329	0.553	0.200	-2.236
DGLS 8	1.128	0.141	0.912	0.363	0.247	-2.582	0.499	0.214	-2.345
DGLS 9	1.159	0.149	1.065	0.223	0.271	-2.868	0.471	0.224	-2.365
DGLS 10	1.170	0.157	1.083	0.960	0.221	-0.182	0.568	0.240	-1.800
DGLS 11	1.198	0.173	1.143	1.059	0.212	0.279	0.684	0.261	-1.209
DGLS 12	1.177	0.166	1.064	1.077	0.220	0.349	0.652	0.277	-1.258
DGLS 13	1.158	0.161	0.984	1.077	0.223	0.345	0.491	0.284	-1.792
DGLS 14	1.181	0.179	1.013	1.054	0.218	0.248	0.461	0.299	-1.802
DGLS 15	1.249	0.215	1.161	0.988	0.237	-0.051	0.364	0.306	-2.078
DGLS 16	1.194	0.208	0.934	0.037	0.396	-2.434	0.386	0.325	-1.890
DGLS 17	1.184	0.217	0.848	-0.043	0.419	-2.487	0.335	0.344	-1.934
DGLS 18	1.219	0.230	0.950	1.036	0.224	0.161	0.317	0.366	-1.866
DGLS 19	1.158	0.224	0.706	1.125	0.184	0.678	0.220	0.378	-2.065
DGLS 20	1.190	0.255	0.746	1.183	0.155	1.183	0.029	0.396	-2.455

Notes

1. The Newey and West (1987) method is employed in the DOLS(p) estimator.
2. An AR(1) model is assumed for the errors in the DGLS(p) estimator.

Table 1E: Estimation Results – Quarterly short-term interest rates

<i>Estimator</i>	<i>UK</i>			<i>US</i>		
	$\hat{\theta}$	<i>s.e.</i> ($\hat{\theta}$)	<i>t-test</i> <i>Ho: $\hat{\theta}=1$</i>	$\hat{\theta}$	<i>s.e.</i> ($\hat{\theta}$)	<i>t-test</i> <i>Ho: $\hat{\theta}=1$</i>
OLS	0.416	0.052	-11.337	0.696	0.092	-3.301
ADL(1,2)	0.912	0.137	-0.645	1.053	0.197	0.267
JOH	1.092	0.105	0.874	1.451	0.174	2.599
FMLS	0.583	0.119	-3.503	0.802	0.149	-1.326
PW-FMLS	0.926	0.149	-0.493	1.218	0.165	1.322
DOLS 1	0.602	0.081	-4.933	0.783	0.100	-2.163
DOLS 2	0.691	0.090	-3.455	0.846	0.109	-1.414
DOLS 3	0.746	0.102	-2.493	0.872	0.114	-1.121
DOLS 4	0.748	0.101	-2.488	0.887	0.122	-0.931
DOLS 5	0.751	0.101	-2.472	0.900	0.129	-0.779
DOLS 6	0.764	0.097	-2.440	0.917	0.134	-0.618
DOLS 7	0.777	0.091	-2.461	0.930	0.140	-0.502
DOLS 8	0.781	0.088	-2.491	0.947	0.146	-0.363
DOLS 9	0.783	0.088	-2.478	0.962	0.148	-0.256
DOLS 10	0.779	0.089	-2.481	0.977	0.150	-0.156
DOLS 11	0.780	0.089	-2.478	0.990	0.154	-0.066
DOLS 12	0.780	0.089	-2.456	1.004	0.157	0.024
DOLS 13	0.781	0.090	-2.442	1.012	0.158	0.077
DOLS 14	0.781	0.090	-2.427	1.025	0.158	0.161
DOLS 15	0.781	0.090	-2.431	1.037	0.160	0.231
DOLS 16	0.783	0.090	-2.408	1.056	0.161	0.346
DOLS 17	0.786	0.090	-2.390	1.077	0.163	0.471
DOLS 18	0.783	0.092	-2.372	1.089	0.165	0.540
DOLS 19	0.779	0.094	-2.348	1.096	0.166	0.581
DOLS 20	0.775	0.096	-2.333	1.110	0.168	0.654
DGLS 1	0.041	0.036	-26.561	0.158	0.059	-14.185
DGLS 2	0.120	0.052	-16.974	0.357	0.094	-6.871
DGLS 3	0.460	0.075	-7.241	0.549	0.116	-3.900
DGLS 4	0.440	0.087	-6.462	0.616	0.133	-2.888
DGLS 5	0.396	0.096	-6.296	0.634	0.143	-2.560
DGLS 6	0.371	0.110	-5.738	0.718	0.152	-1.863
DGLS 7	0.578	0.121	-3.478	0.687	0.162	-1.936
DGLS 8	0.710	0.120	-2.413	0.737	0.170	-1.547
DGLS 9	0.835	0.118	-1.402	0.761	0.179	-1.339
DGLS 10	0.736	0.132	-1.996	0.746	0.192	-1.324
DGLS 11	0.712	0.146	-1.972	0.704	0.208	-1.423
DGLS 12	0.789	0.142	-1.491	0.827	0.214	-0.809
DGLS 13	0.800	0.146	-1.373	0.826	0.225	-0.772
DGLS 14	0.852	0.145	-1.020	0.877	0.233	-0.528
DGLS 15	0.892	0.151	-0.716	0.772	0.257	-0.887
DGLS 16	0.907	0.160	-0.584	0.718	0.277	-1.021
DGLS 17	0.890	0.161	-0.686	0.981	0.253	-0.074
DGLS 18	0.885	0.162	-0.709	1.075	0.257	0.291
DGLS 19	0.910	0.172	-0.524	1.025	0.270	0.092
DGLS 20	0.962	0.200	-0.191	1.026	0.279	0.092

Notes

1. The Newey and West (1987) method is employed in the DOLS(p) estimator.
2. An AR(1) model is assumed for the errors in the DGLS(p) estimator.

Table 2A: Estimation Results – Annual long-term interest rates

<i>Estimator</i>	<i>Australia</i>			<i>Belgium</i>			<i>Canada</i>		
	$\hat{\theta}$	<i>s.e</i> ($\hat{\theta}$)	<i>t-test</i> <i>Ho: $\hat{\theta}=1$</i>	$\hat{\theta}$	<i>s.e</i> ($\hat{\theta}$)	<i>t-test</i> <i>Ho: $\hat{\theta}=1$</i>	$\hat{\theta}$	<i>s.e</i> ($\hat{\theta}$)	<i>t-test</i> <i>Ho: $\hat{\theta}=1$</i>
OLS	0.251	0.185	-4.062	0.450	0.165	-3.345	0.574	0.151	-2.821
ADL(1,2)	1.166	0.353	0.469	0.761	0.356	-0.672	1.032	0.254	0.126
JOH	1.561	0.313	1.792	1.779	0.372	2.093	1.068	0.178	0.384
FMLS	0.368	0.170	-3.717	0.714	0.128	-2.241	0.900	0.215	-0.464
PW-FMLS	1.337	0.296	1.140	1.007	0.203	0.032	1.234	0.205	1.142
DOLS 1	0.314	0.197	-3.488	0.535	0.193	-2.415	0.661	0.141	-2.398
DOLS 2	0.507	0.160	-3.083	0.598	0.214	-1.879	0.734	0.144	-1.841
DOLS 3	0.623	0.172	-2.190	0.641	0.210	-1.713	0.826	0.148	-1.175
DOLS 4	0.687	0.178	-1.761	0.710	0.202	-1.434	0.856	0.132	-1.092
DOLS 5	0.745	0.173	-1.472	0.760	0.178	-1.344	0.882	0.107	-1.097
DOLS 6	0.814	0.149	-1.249	0.827	0.140	-1.238	0.909	0.082	-1.099
DOLS 7	0.898	0.125	-0.817	0.887	0.108	-1.043	0.932	0.080	-0.856
DOLS 8	0.955	0.106	-0.429	0.914	0.097	-0.890	0.961	0.089	-0.436
DOLS 9	1.019	0.090	0.209	0.949	0.089	-0.574	0.963	0.085	-0.438
DOLS 10	1.067	0.090	0.744	0.968	0.097	-0.334	0.964	0.089	-0.407
DOLS 11	1.106	0.083	1.284	0.962	0.119	-0.325	0.981	0.101	-0.193
DOLS 12	1.117	0.082	1.435	0.955	0.141	-0.321	0.989	0.104	-0.109
DOLS 13	1.125	0.097	1.286	0.924	0.171	-0.445	1.039	0.119	0.326
DOLS 14	1.144	0.117	1.230	0.911	0.197	-0.451	1.083	0.147	0.561
DOLS 15	1.146	0.153	0.954	0.856	0.215	-0.669	1.082	0.178	0.462
DOLS 16	1.151	0.154	0.981	0.781	0.211	-1.039	1.088	0.209	0.419
DOLS 17	1.176	0.160	1.098	0.820	0.235	-0.767	1.096	0.234	0.409
DOLS 18	1.192	0.165	1.162	0.883	0.254	-0.463	1.071	0.259	0.273
DOLS 19	1.271	0.182	1.491	1.030	0.312	0.097	1.110	0.333	0.330
DOLS 20	1.220	0.233	0.941	1.268	0.373	0.719	1.193	0.411	0.470
DGLS 1	0.174	0.058	-14.216	0.212	0.075	-10.572	0.234	0.083	-9.285
DGLS 2	0.298	0.089	-7.887	0.355	0.110	-5.882	0.441	0.110	-5.065
DGLS 3	0.315	0.115	-5.982	0.276	0.128	-5.635	0.579	0.130	-3.231
DGLS 4	0.388	0.137	-4.469	0.243	0.186	-4.079	0.633	0.161	-2.278
DGLS 5	0.385	0.161	-3.825	0.223	0.224	-3.479	0.700	0.163	-1.843
DGLS 6	0.448	0.174	-3.169	0.436	0.243	-2.327	0.791	0.173	-1.207
DGLS 7	0.659	0.174	-1.961	0.785	0.201	-1.071	0.859	0.160	-0.885
DGLS 8	0.808	0.143	-1.343	0.812	0.213	-0.886	0.916	0.104	-0.810
DGLS 9	0.955	0.104	-0.437	0.924	0.158	-0.480	0.925	0.101	-0.736
DGLS 10	1.050	0.079	0.634	1.046	0.163	0.284	0.971	0.125	-0.232
DGLS 11	1.110	0.075	1.472	1.088	0.175	0.501	0.988	0.131	-0.091
DGLS 12	1.113	0.082	1.378	0.971	0.189	-0.156	0.983	0.148	-0.116
DGLS 13	1.115	0.088	1.306	0.974	0.218	-0.122	1.058	0.163	0.358
DGLS 14	1.138	0.099	1.387	1.090	0.244	0.367	1.085	0.177	0.481
DGLS 15	1.141	0.105	1.337	1.036	0.268	0.133	1.088	0.197	0.448
DGLS 16	1.135	0.127	1.062	0.969	0.318	-0.099	1.126	0.241	0.523
DGLS 17	1.163	0.157	1.041	1.000	0.365	0.000	1.151	0.267	0.565
DGLS 18	1.170	0.192	0.885	1.015	0.456	0.033	1.196	0.334	0.586
DGLS 19	1.279	0.236	1.182	1.452	0.414	1.091	1.408	0.407	1.002
DGLS 20	1.334	0.267	1.252	1.912	0.414	2.205	1.579	0.530	1.092

Notes

1. The Newey and West (1987) method is employed in the DOLS(p) estimator.
2. An AR(1) model is assumed for the errors in the DGLS(p) estimator.

Table 2B: Estimation Results – Annual long-term interest rates

<i>Country</i>	<i>France</i>			<i>Germany</i>			<i>Ireland</i>		
	$\hat{\theta}$	<i>s.e.</i> ($\hat{\theta}$)	<i>t-test</i> $H_0: \hat{\theta}=1$	$\hat{\theta}$	<i>s.e.</i> ($\hat{\theta}$)	<i>t-test</i> $H_0: \hat{\theta}=1$	$\hat{\theta}$	<i>s.e.</i> ($\hat{\theta}$)	<i>t-test</i> $H_0: \hat{\theta}=1$
OLS	0.334	0.151	-4.425	0.615	0.092	-4.196	0.551	0.054	-8.295
ADL(1,2)	0.767	0.283	-0.824	0.675	0.205	-1.587	0.686	0.127	-2.470
JOH	1.185	0.186	0.996	0.818	0.1383	-1.317	0.892	0.109	-0.993
FMLS	0.515	0.143	-3.397	1.136	0.277	0.490	0.833	0.156	-1.071
PW-FMLS	0.870	0.168	-0.772	1.622	0.303	2.052	1.047	0.158	0.299
DOLS 1	0.421	0.170	-3.398	0.645	0.098	-3.614	0.577	0.060	-7.064
DOLS 2	0.529	0.157	-3.002	0.662	0.119	-2.844	0.646	0.069	-5.138
DOLS 3	0.640	0.142	-2.541	0.613	0.130	-2.973	0.687	0.068	-4.588
DOLS 4	0.674	0.136	-2.392	0.574	0.147	-2.902	0.706	0.065	-4.554
DOLS 5	0.729	0.134	-2.032	0.604	0.151	-2.629	0.726	0.062	-4.440
DOLS 6	0.778	0.132	-1.687	0.618	0.144	-2.643	0.730	0.060	-4.520
DOLS 7	0.810	0.133	-1.424	0.653	0.145	-2.399	0.754	0.057	-4.337
DOLS 8	0.836	0.135	-1.218	0.705	0.131	-2.252	0.774	0.054	-4.195
DOLS 9	0.947	0.136	-0.389	0.766	0.119	-1.971	0.780	0.052	-4.208
DOLS 10	0.994	0.124	-0.049	0.813	0.135	-1.393	0.813	0.054	-3.446
DOLS 11	1.043	0.125	0.341	0.842	0.164	-0.963	0.842	0.056	-2.843
DOLS 12	1.082	0.134	0.614	0.811	0.200	-0.949	0.866	0.061	-2.188
DOLS 13	1.114	0.145	0.782	0.793	0.269	-0.768	0.864	0.075	-1.805
DOLS 14	1.105	0.147	0.715	0.847	0.322	-0.477	0.927	0.099	-0.732
DOLS 15	1.131	0.163	0.800	0.889	0.397	-0.281	0.884	0.119	-0.976
DOLS 16	1.131	0.161	0.814	0.852	0.480	-0.309	0.857	0.089	-1.611
DOLS 17	0.997	0.177	-0.020	0.769	0.474	-0.487	0.804	0.093	-2.116
DOLS 18	1.068	0.217	0.313	0.776	0.394	-0.569	0.806	0.094	-2.067
DOLS 19	1.178	0.227	0.784	1.149	0.248	0.599	0.727	0.124	-2.203
DOLS 20	1.478	0.255	1.872	1.141	0.216	0.652	0.755	0.164	-1.500
DGLS 1	0.147	0.063	-13.457	0.567	0.126	-3.436	0.319	0.087	-7.809
DGLS 2	0.255	0.089	-8.395	0.698	0.149	-2.036	0.367	0.108	-5.886
DGLS 3	0.392	0.117	-5.218	0.646	0.167	-2.128	0.534	0.110	-4.222
DGLS 4	0.372	0.140	-4.485	0.523	0.180	-2.651	0.612	0.104	-3.746
DGLS 5	0.441	0.171	-3.270	0.519	0.195	-2.464	0.683	0.095	-3.335
DGLS 6	0.639	0.184	-1.970	0.569	0.220	-1.965	0.675	0.095	-3.411
DGLS 7	0.695	0.191	-1.595	0.510	0.258	-1.896	0.699	0.081	-3.694
DGLS 8	0.777	0.134	-1.672	0.640	0.265	-1.361	0.738	0.071	-3.689
DGLS 9	0.857	0.143	-1.000	0.709	0.275	-1.058	0.751	0.070	-3.552
DGLS 10	0.891	0.173	-0.629	0.823	0.284	-0.625	0.795	0.069	-2.988
DGLS 11	0.968	0.146	-0.222	0.794	0.292	-0.706	0.820	0.074	-2.445
DGLS 12	1.028	0.132	0.212	0.769	0.318	-0.725	0.845	0.080	-1.952
DGLS 13	1.092	0.144	0.639	0.744	0.385	-0.665	0.844	0.092	-1.693
DGLS 14	1.060	0.175	0.343	0.730	0.420	-0.643	0.887	0.116	-0.976
DGLS 15	1.046	0.168	0.273	0.903	0.535	-0.181	0.863	0.099	-1.382
DGLS 16	1.104	0.196	0.530	1.017	0.578	0.030	0.834	0.110	-1.503
DGLS 17	1.049	0.247	0.200	0.976	0.500	-0.049	0.831	0.131	-1.296
DGLS 18	1.013	0.343	0.039	1.365	0.420	0.869	0.777	0.146	-1.532
DGLS 19	0.844	0.501	-0.310	1.590	0.571	1.035	0.759	0.188	-1.285
DGLS 20	1.108	0.533	0.202	1.273	0.526	0.520	0.928	0.191	-0.376

Notes

1. The Newey and West (1987) method is employed in the DOLS(p) estimator.
2. An AR(1) model is assumed for the errors in the DGLS(p) estimator.

Table 2C: Estimation Results – Annual long-term interest rates

<i>Country</i>	<i>Italy</i>			<i>Netherlands</i>			<i>Norway</i>		
	$\hat{\theta}$	<i>s.e.</i> ($\hat{\theta}$)	<i>t-test</i> <i>Ho: $\hat{\theta}=1$</i>	$\hat{\theta}$	<i>s.e.</i> ($\hat{\theta}$)	<i>t-test</i> <i>Ho: $\hat{\theta}=1$</i>	$\hat{\theta}$	<i>s.e.</i> ($\hat{\theta}$)	<i>t-test</i> <i>Ho: $\hat{\theta}=1$</i>
OLS	0.539	0.123	-3.751	0.238	0.148	-5.161	0.309	0.184	-3.763
ADL(1,2)	0.862	0.149	-0.927	0.665	0.338	-0.993	1.358	0.598	0.599
JOH	0.789	0.126	-1.679	0.992	0.273	1.763	1.231	0.253	0.913
FMLS	0.680	0.079	-4.030	0.490	0.193	-2.643	0.464	0.155	-3.468
PW-FMLS	0.765	0.114	-2.061	1.062	0.263	0.234	1.490	0.320	1.530
DOLS 1	0.623	0.113	-3.337	0.332	0.149	-4.492	0.394	0.229	-2.645
DOLS 2	0.672	0.104	-3.163	0.463	0.145	-3.707	0.524	0.216	-2.201
DOLS 3	0.695	0.092	-3.306	0.473	0.161	-3.276	0.665	0.210	-1.595
DOLS 4	0.708	0.079	-3.695	0.486	0.184	-2.791	0.778	0.210	-1.057
DOLS 5	0.734	0.073	-3.663	0.539	0.197	-2.343	0.867	0.204	-0.653
DOLS 6	0.770	0.071	-3.256	0.576	0.195	-2.174	0.945	0.191	-0.288
DOLS 7	0.805	0.071	-2.749	0.599	0.188	-2.140	1.018	0.177	0.104
DOLS 8	0.827	0.070	-2.464	0.639	0.184	-1.960	1.083	0.157	0.531
DOLS 9	0.836	0.072	-2.295	0.683	0.174	-1.821	1.156	0.135	1.155
DOLS 10	0.839	0.086	-1.876	0.717	0.162	-1.742	1.217	0.125	1.738
DOLS 11	0.853	0.109	-1.344	0.702	0.156	-1.916	1.257	0.132	1.957
DOLS 12	0.876	0.134	-0.931	0.705	0.151	-1.950	1.313	0.143	2.191
DOLS 13	0.907	0.144	-0.646	0.698	0.155	-1.954	1.358	0.178	2.018
DOLS 14	0.932	0.144	-0.476	0.738	0.169	-1.551	1.415	0.217	1.914
DOLS 15	0.974	0.147	-0.180	0.880	0.151	-0.796	1.412	0.250	1.646
DOLS 16	1.019	0.167	0.114	1.027	0.166	0.165	1.462	0.310	1.490
DOLS 17	1.024	0.206	0.114	1.184	0.179	1.027	1.553	0.418	1.323
DOLS 18	1.027	0.268	0.100	1.403	0.196	2.054	1.776	0.654	1.186
DOLS 19	1.088	0.309	0.286	1.900	0.266	3.390	1.845	0.830	1.019
DOLS 20	1.171	0.369	0.464	2.336	0.188	7.113	2.006	0.894	1.125
DGLS 1	0.343	0.084	-7.871	0.211	0.077	-10.277	0.131	0.052	-16.653
DGLS 2	0.642	0.102	-3.531	0.361	0.116	-5.494	0.252	0.084	-8.945
DGLS 3	0.664	0.112	-3.004	0.325	0.145	-4.658	0.278	0.119	-6.082
DGLS 4	0.645	0.131	-2.704	0.189	0.172	-4.728	0.310	0.152	-4.559
DGLS 5	0.660	0.152	-2.235	0.346	0.192	-3.400	0.505	0.187	-2.653
DGLS 6	0.716	0.161	-1.767	0.424	0.207	-2.785	0.648	0.197	-1.790
DGLS 7	0.807	0.139	-1.387	0.450	0.232	-2.372	0.731	0.219	-1.224
DGLS 8	0.877	0.145	-0.847	0.410	0.268	-2.205	0.818	0.235	-0.776
DGLS 9	0.869	0.156	-0.843	0.493	0.253	-2.009	0.893	0.246	-0.435
DGLS 10	0.842	0.175	-0.903	0.638	0.214	-1.689	1.023	0.199	0.115
DGLS 11	0.877	0.187	-0.655	0.628	0.218	-1.706	1.044	0.217	0.201
DGLS 12	0.878	0.204	-0.601	0.653	0.231	-1.506	1.100	0.227	0.442
DGLS 13	0.874	0.215	-0.588	0.625	0.230	-1.632	1.161	0.239	0.673
DGLS 14	0.842	0.236	-0.670	0.606	0.263	-1.501	1.267	0.270	0.989
DGLS 15	0.990	0.254	-0.038	0.838	0.220	-0.737	1.237	0.311	0.761
DGLS 16	1.060	0.267	0.224	0.945	0.248	-0.222	1.262	0.351	0.746
DGLS 17	1.056	0.314	0.177	1.084	0.287	0.291	1.254	0.415	0.611
DGLS 18	1.186	0.372	0.499	1.121	0.334	0.362	1.303	0.584	0.519
DGLS 19	1.488	0.381	1.283	2.017	0.238	4.270	1.320	0.814	0.394
DGLS 20	1.897	0.504	1.778	2.285	0.312	4.120	1.633	1.045	0.606

Notes

1. The Newey and West (1987) method is employed in the DOLS(p) estimator.
2. An AR(1) model is assumed for the errors in the DGLS(p) estimator.

Table 2D: Estimation Results – Annual long-term interest rates

Country	Portugal			Sweden			Switzerland		
	$\hat{\theta}$	<i>s.e</i> ($\hat{\theta}$)	<i>t-test</i> $H_0: \hat{\theta}=1$	$\hat{\theta}$	<i>s.e</i> ($\hat{\theta}$)	<i>t-test</i> $H_0: \hat{\theta}=1$	$\hat{\theta}$	<i>s.e</i> ($\hat{\theta}$)	<i>t-test</i> $H_0: \hat{\theta}=1$
OLS	0.514	0.115	-4.214	0.470	0.167	-3.181	0.356	0.038	-16.757
ADL(1,2)	0.932	0.207	-0.327	0.866	0.541	-0.248	0.467	0.100	-5.365
JOH	0.957	0.180	-0.238	1.308	0.267	1.154	0.843	0.108	-1.457
FMLS	0.605	0.043	-9.200	0.951	0.191	-0.257	0.556	0.085	-5.254
PW-FMLS	0.752	0.134	-1.841	1.275	0.218	1.262	0.626	0.085	-4.408
DOLS 1	0.570	0.097	-4.418	0.623	0.162	-2.329	0.415	0.034	-17.210
DOLS 2	0.603	0.085	-4.665	0.777	0.138	-1.618	0.462	0.041	-13.022
DOLS 3	0.631	0.076	-4.876	0.932	0.131	-0.520	0.493	0.039	-12.941
DOLS 4	0.668	0.056	-5.915	1.007	0.129	0.051	0.498	0.045	-11.171
DOLS 5	0.695	0.039	-7.925	1.039	0.114	0.342	0.492	0.056	-9.103
DOLS 6	0.724	0.028	-10.023	1.064	0.103	0.618	0.494	0.063	-7.989
DOLS 7	0.743	0.027	-9.545	1.089	0.094	0.946	0.495	0.075	-6.747
DOLS 8	0.756	0.031	-7.815	1.101	0.092	1.103	0.515	0.088	-5.493
DOLS 9	0.767	0.036	-6.454	1.130	0.094	1.391	0.538	0.100	-4.602
DOLS 10	0.784	0.042	-5.183	1.133	0.089	1.490	0.521	0.119	-4.041
DOLS 11	0.782	0.046	-4.703	1.108	0.082	1.319	0.532	0.133	-3.533
DOLS 12	0.764	0.052	-4.543	1.125	0.094	1.328	0.528	0.132	-3.579
DOLS 13	0.763	0.061	-3.870	1.096	0.084	1.144	0.505	0.132	-3.765
DOLS 14	0.759	0.068	-3.571	1.097	0.087	1.123	0.496	0.132	-3.829
DOLS 15	0.780	0.070	-3.162	1.100	0.113	0.882	0.478	0.126	-4.146
DOLS 16	0.805	0.081	-2.407	1.078	0.142	0.546	0.473	0.160	-3.301
DOLS 17	0.817	0.105	-1.752	1.225	0.090	2.496	0.503	0.175	-2.851
DOLS 18	0.812	0.120	-1.571	1.334	0.065	5.118	0.518	0.159	-3.042
DOLS 19	0.805	0.104	-1.875	1.348	0.076	4.569	0.539	0.219	-2.108
DOLS 20	0.807	0.091	-2.136	1.330	0.127	2.588	0.562	0.237	-1.854
DGLS 1	0.363	0.073	-8.769	0.094	0.059	-15.428	0.292	0.065	-10.891
DGLS 2	0.461	0.096	-5.620	0.195	0.100	-8.032	0.367	0.075	-8.435
DGLS 3	0.432	0.118	-4.818	0.145	0.146	-5.848	0.413	0.082	-7.201
DGLS 4	0.522	0.148	-3.234	0.285	0.194	-3.688	0.439	0.096	-5.855
DGLS 5	0.554	0.169	-2.646	0.366	0.239	-2.655	0.402	0.113	-5.288
DGLS 6	0.729	0.177	-1.530	0.395	0.265	-2.282	0.416	0.124	-4.728
DGLS 7	0.804	0.154	-1.275	0.855	0.173	-0.838	0.430	0.137	-4.173
DGLS 8	0.836	0.152	-1.081	0.886	0.189	-0.600	0.477	0.145	-3.622
DGLS 9	0.835	0.174	-0.947	1.010	0.114	0.086	0.483	0.161	-3.218
DGLS 10	0.882	0.133	-0.887	1.059	0.114	0.512	0.518	0.180	-2.679
DGLS 11	0.899	0.139	-0.727	1.033	0.114	0.284	0.432	0.205	-2.772
DGLS 12	0.900	0.148	-0.674	1.043	0.098	0.436	0.384	0.202	-3.059
DGLS 13	0.981	0.195	-0.100	1.064	0.095	0.673	0.419	0.208	-2.797
DGLS 14	0.932	0.216	-0.317	1.086	0.099	0.869	0.345	0.223	-2.938
DGLS 15	0.871	0.240	-0.539	1.093	0.109	0.850	0.345	0.217	-3.024
DGLS 16	1.056	0.467	0.119	1.011	0.148	0.072	0.373	0.222	-2.818
DGLS 17	1.510	0.517	0.987	1.250	0.092	2.711	0.399	0.192	-3.133
DGLS 18	2.069	0.403	2.652	1.337	0.047	7.154	0.491	0.195	-2.615
DGLS 19	2.122	0.490	2.289	1.351	0.067	5.276	0.622	0.235	-1.607
DGLS 20	1.795	0.621	1.280	1.328	0.142	2.315	0.740	0.182	-1.430

Notes

1. The Newey and West (1987) method is employed in the DOLS(p) estimator.
2. An AR(1) model is assumed for the errors in the DGLS(p) estimator.

Table 2E: Estimation Results – Annual long-term interest rates

<i>Estimator</i>	<i>UK</i>			<i>US</i>		
	$\hat{\theta}$	<i>s.e.</i> ($\hat{\theta}$)	<i>t-test</i> <i>Ho: $\hat{\theta}=1$</i>	$\hat{\theta}$	<i>s.e.</i> ($\hat{\theta}$)	<i>t-test</i> <i>Ho: $\hat{\theta}=1$</i>
OLS	0.525	0.055	-8.710	0.608	0.120	-3.285
ADL(1,2)	0.580	0.196	-2.145	1.126	0.215	0.587
JOH	1.015	0.142	0.109	1.199	0.187	1.072
FMLS	0.743	0.137	-1.873	1.020	0.241	0.081
PW-FMLS	0.986	0.122	-0.115	1.435	0.255	1.704
DOLS 1	0.576	0.063	-6.748	0.701	0.109	-2.754
DOLS 2	0.606	0.072	-5.469	0.818	0.125	-1.455
DOLS 3	0.638	0.066	-5.476	0.874	0.124	-1.022
DOLS 4	0.657	0.062	-5.526	0.936	0.121	-0.526
DOLS 5	0.670	0.061	-5.423	0.974	0.112	-0.230
DOLS 6	0.691	0.058	-5.359	0.987	0.098	-0.136
DOLS 7	0.705	0.053	-5.605	1.015	0.093	0.164
DOLS 8	0.709	0.054	-5.379	1.050	0.097	0.513
DOLS 9	0.705	0.058	-5.137	1.065	0.096	0.681
DOLS 10	0.708	0.057	-5.098	1.079	0.093	0.848
DOLS 11	0.715	0.064	-4.469	1.093	0.101	0.923
DOLS 12	0.738	0.072	-3.639	1.081	0.094	0.870
DOLS 13	0.752	0.080	-3.096	1.046	0.089	0.521
DOLS 14	0.754	0.092	-2.675	1.074	0.104	0.712
DOLS 15	0.769	0.106	-2.173	1.094	0.133	0.704
DOLS 16	0.769	0.124	-1.867	1.073	0.155	0.470
DOLS 17	0.745	0.136	-1.878	1.078	0.165	0.473
DOLS 18	0.684	0.132	-2.392	1.068	0.212	0.323
DOLS 19	0.576	0.135	-3.144	1.026	0.282	0.091
DOLS 20	0.417	0.112	-5.193	1.048	0.324	0.148
DGLS 1	0.254	0.054	-13.827	0.360	0.096	-6.677
DGLS 2	0.274	0.075	-9.667	0.488	0.135	-3.795
DGLS 3	0.253	0.101	-7.388	0.623	0.143	-2.642
DGLS 4	0.321	0.123	-5.511	0.866	0.172	-0.782
DGLS 5	0.467	0.123	-4.334	0.919	0.181	-0.449
DGLS 6	0.550	0.120	-3.758	0.911	0.197	-0.451
DGLS 7	0.585	0.118	-3.506	0.989	0.204	-0.053
DGLS 8	0.603	0.123	-3.220	1.082	0.173	0.474
DGLS 9	0.599	0.128	-3.120	1.041	0.154	0.267
DGLS 10	0.609	0.133	-2.934	1.177	0.193	0.917
DGLS 11	0.578	0.161	-2.616	1.222	0.198	1.124
DGLS 12	0.571	0.187	-2.302	1.114	0.174	0.657
DGLS 13	0.625	0.183	-2.052	1.250	0.361	0.693
DGLS 14	0.607	0.191	-2.055	1.262	0.365	0.718
DGLS 15	0.647	0.208	-1.701	1.419	0.331	1.263
DGLS 16	0.674	0.255	-1.279	1.456	0.367	1.244
DGLS 17	0.671	0.315	-1.045	1.427	0.428	0.996
DGLS 18	0.639	0.304	-1.187	1.499	0.472	1.058
DGLS 19	0.566	0.323	-1.343	1.755	0.381	1.982
DGLS 20	0.450	0.410	-1.341	1.680	0.486	1.400

Notes

1. The Newey and West (1987) method is employed in the DOLS(p) estimator.
2. An AR(1) model is assumed for the errors in the DGLS(p) estimator.