Inflation targeting and interest rates

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March 2013

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Abstract: Inflation Targeting (*IT*) can be expected to play a role in structurally reducing nominal interest rates, by lowering a country's inflation expectations and risk premium. Relying on a panel of 52 advanced and emerging economies over the 1975-2009 years, we carry out a formal investigation of this hypothesis. Our econometric strategy adopts a flexible and efficient panel estimation framework, controlling for a number of issues usually neglected in the literature, such as parameter heterogeneity and cross-section dependence. Our findings are supportive of the optimistic view on *IT*, indicating that adoption of this monetary regime leads to lower nominal interest rates.

Keywords: Inflation targeting, Interest rates, panel data, multifactor modeling.

JEL Classification: C23, E42, E43, E52, E58.

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1. **Introduction**

Inflation Targeting (*IT*) has been around monetary policymaking for a quarter of a century now, and yet the dispute over its true effects on macroeconomic performance is far from settled. Several studies have provided support for the hypothesis that *IT* improves macroeconomic performance, as measured by lower inflation rates and reduced inflation and/or output volatilities (e.g. Mishkin and Schmidt-Hebbel, 2007; Vega and Winkelried, 2005; Gonçalves and Salles, 2008).[1] However, there is also a large amount of contrasting empirical evidence in the literature, such as that provided by Ball and Sheridan (2005), Lin and Ye (2007) and Brito and Bystedt (2010). These studies offer a different view on the subject, arguing that the evidence of beneficial effects of *IT* implementation is not clear-cut.

An important aspect of this debate regards the potential role played by *IT* in structurally reducing nominal interest rates. The literature on the determinants of nominal interest rate differentials largely points to significant effects associated to policy credibility and economic institutions (e.g. Bernhardsen, 2000; Tillmann, 2003). In turn, this suggests that interest rate determination may be regime-dependent and, in particular, positively affected by *IT*. The intuition is that the more credible this policy strategy, the better anchored inflation expectations should be to the official target, and thus the lower the nominal interest rate required to maintain price stability. Therefore, testing for possible effects of *IT* in reducing nominal interest rates is also an indirect assessment of its overall credibility as a monetary policy framework.[2]

Mishkin and Schmidt-Hebbel (2007), Gonçalves and Salles (2008) and Ball and Sheridan (2005), among others, have pointed out that a common stylised fact for countries which adopted *IT* is a decline in interest rate levels. However, the empirical evidence on the significance of this relationship is not conclusive. For instance, Lin and Ye (2007) rely on a propensity score matching approach to assess the treatment effect of *IT* and their results do not provide support for the

[1] There is also some evidence of *IT* improving the inflation-output trade-off, as in Clifton, Leon and Wong (2001).
[2] For a direct assessment of the credibility effects of *IT*, see Lanzafame and Nogueira (2011).

hypothesis that *IT* reduces interest rates. Similarly, using a difference-in-differences approach, Ball and Sheridan (2005) find that *IT* has no significant effect on long-term nominal interest rates. They argue that the fall in interest rates observed after *IT* adoption depends on a "reversion to the mean" phenomenon, as countries implementing *IT* tend to have rather high interest rates before the formal introduction of this policy framework. Nevertheless, as noted by Brito and Bystedt (2010), these findings are subject to some important limitations. Both papers focus solely on developed countries, which restricts the general applicability of their conclusions. Furthermore, though dealing with self-selection issues, Lin and Ye's (2007) methodology does not control for time trends and possible unobservable characteristics of the countries under examination. Meanwhile, Ball and Sheridan's (2005) approach does not account for endogeneity nor control for time or country fixed effects.

A further recent study by Fouejieu and Roger (2013) deals with one of these drawbacks, relying on system GMM techniques (Blundell and Bond, 1998) to control for endogeneity, and provides different results. Specifically, Fouejieu and Roger (2013) investigate the impact of *IT* on cross-country interest rate differentials and find that, by reducing policy uncertainty, *IT* leads to a decline in spreads. In this paper we conduct a similar exercise, using panel methods to investigate empirically the hypothesis that *IT* adoption is associated with lower nominal interest rates. Our approach, however, has several advantages with respect to that used by Fouejieu and Roger (2013).

Relying on a panel of annual data on advanced and emerging economies, our empirical analysis makes a number of contributions to the literature. Studies on the role of *IT* are typically based on the cross-section estimation methodology developed by Ball and Sheridan (2005) or, at best, make use of standard panel techniques to control for variable endogeneity (e.g. Fouejieu and Roger, 2013; Brito and Bysted, 2010; Mishkin and Schmidt-Hebbel, 2007). Contrary to this, this paper adopts a more flexible and efficient panel estimation framework, controlling for a number of issues affecting panel methods which are usually neglected in the literature. Among these, parameter heterogeneity and cross-section dependence among the panel groups are of particular importance. Standard panel techniques (e.g. the pooled, fixed-effects or GMM estimators) impose a high degree of parameter homogeneity but, as a result of different economic structures, economic policy frameworks and other characteristics, the effects of *IT* are likely to be heterogeneous across countries. In such a case, standard panel estimators are thus fundamentally misspecified and will yield biased results (Pesaran and Smith, 1995). Meanwhile, cross-section dependence can arise in panels from the presence of common factors. Advanced and emerging economies interact via economic, trade, political and other channels and are affected by common phenomena, such as the recent financial crisis and the subsequent so-called 'Lesser Depression'. This is likely to result in cross-section correlation in a cross-country panel, which leads to biased estimates and incorrect inference in standard panel estimators based on the assumption of cross-section independence (Pesaran, 2006). Our empirical strategy deals with these issues by making use of mean-group estimation and multifactor modelling. Specifically, we rely on the traditional mean-group (MG) estimator (Pesaran and Smith, 1995), as well as two recently-developed multifactor modelling approaches – the 'Common Correlated Effects Mean Group' (CCEMG) estimator put forward by Pesaran (2006) and the 'Augmented Mean Group' (AMG) technique developed by Eberhardt and Teal (2012b). The MG approach allows for parameter heterogeneity and country-specific elements while, in addition, the CCEMG and AMG estimators also control for cross-section dependence arising from common factors.

The CCEMG and AMG estimators can also accommodate variable endogeneity when this arises from common factors driving both the dependent and independent variables. However, as mentioned, recent studies suggest that *IT* adoption may subject to a different type of endogeneity, at least when it represents a policy response to unsatisfactory macroeconomic performance (e.g. Brito and Bystedt, 2010; Lanzafame and Nogueira, 2011). We take account of this and other possible drawbacks of our empirical analysis subjecting our findings to a series of robustness checks.

The remainder of this paper is organised as follows. The model and the empirical methodology are illustrated in Section 2. The data are described in Section 3, which also carries out a first set of estimations and discusses the results. Section 4 is devoted to the sensitivity analysis and robustness checks. Finally, Section 5 concludes.

2. **Model and empirical methodology**

In the polar case of a small open economy, the uncovered interest parity (UIP) condition implies that the nominal interest rate will depend solely on the foreign interest rate and the expected rate of depreciation. Expressing the nominal exchange rate as the domestic currency price of a unit of foreign exchange, the risk-adjusted UIP condition can be formalised as:

$$r_t = r_t^* + e_t^e + \sigma_t \tag{1}$$

where r_t and r_t^* are, respectively, the domestic and foreign nominal interest rates, e_t^e is the expected rate of depreciation of the domestic currency and σ_t is a (time-varying) risk premium. The relative Purchasing Power Parity (PPP) condition implies

$$e_t = \pi_t - \pi_t^* \tag{2}$$

That is, higher domestic inflation leads to a depreciation. Thus, expected depreciation at time *t* is

$$e_t^e = \pi_t^e - \pi_t^{*e} \tag{3}$$

Adopting a common simple specification (see Edwards and Khan, 1985), the risk premium can be modelled as a constant plus a random term. For domestic inflation, the usual assumption in the literature (e.g. Aisen and Hauner, 2008) is that of an extreme form of adaptive expectations, so that

$$\pi_t^e = \pi_t + \upsilon_t \tag{4}$$

where υ_t is a random error term. However, theory on *IT* implies that both expected inflation and the risk premium will also be a function of the monetary regime (e.g. Fouejieu and Roger, 2013). To capture this, we formalise both π_t^e and σ_t as linear functions of *IT*:

$$\pi_t^e = \pi_t + \lambda_1 IT_t + \upsilon_t \tag{5}$$

$$\sigma_t = \alpha + \lambda_2 IT_t + \nu_t \tag{6}$$

where ν_t is a random error term, both λ_1 and λ_2 are expected to be negative and IT_t is a dummy variable equal to 1 if the country is an inflation-targeter for more than two quarters in year *t* and 0 otherwise. Assuming that the foreign inflation rate can be described as in (4) and using (5) into (3) we get

$$e_t^e = \pi_t - \pi_t^* + \lambda_1 IT_t + \xi_t \tag{7}$$

And, by equation (2)

$$e_t^e = e_t + \lambda_1 IT_t + \xi_t \tag{8}$$

Using this result and (6) in UIP, for estimation purposes we can formalise the following panel model

$$r_{it} = \alpha_i + \beta_i r_{it}^* + \vartheta_i e_{it} + \lambda_i^* IT_{it} + \zeta_{it} \tag{9}$$

where $i = 1,2,...,N$ indicates the cross-sections (groups), $t = 1,2,...,T$ the time periods and $\lambda_i^* = \lambda_{1i} + \lambda_{2i}$. UIP implies that, controlling for expected exchange rate depreciation and risk, the interest rate on domestic and foreign assets should be the same, i.e. $\beta = 1$.

2.1. **Estimation framework**

Our empirical methodology is based on a multifactor-factor modelling approach. Following Eberhardt and Teal (2012a, 2012b), for $i = 1,2,...,N$, $t = 1,2,...,T$ and $m = 1,2,...,k$, let

$$r_{it} = \omega_i + \lambda_i' X_{it} + u_{it} \qquad u_{it} = \phi_i' f_t + \varepsilon_{it} \tag{10}$$

$$X_{mit} = \pi_{mi} + \varphi_{mi}' g_{mt} + \vartheta_{1mi} f_{1mt} + ...\vartheta_{nmi} f_{nmt} + \eta_{mit} \tag{11}$$

$$f_t = o' f_{t-1} + \varsigma_t \qquad \text{and} \qquad g_t = \kappa' g_{t-1} + \varsigma_t \tag{12}$$

where, as in (9), the *m* observed regressors X_{it} in the model are r_{it}^*, e_{it} and IT_{it}, $f_{\cdot mt} \subset f_t$ and the error term ε_{it} is independently distributed with zero mean and variance σ^2. In this setup, cross-section dependence is captured by a set of unobservable common factors f_t, with country-specific factor loadings ϕ_i. The empirical representation of X_{mit} as driven by sets of common factors g_{mt} and f_{nmt} allows for its potential endogeneity, as f_{nmt} may represent a subset of the common factors f_t driving r_{it}. The factors g_{mt} and f_{nmt} can be persistent over time or even nonstationary ($o = 1$, $\kappa = 1$), which allows for potential nonstationarity in X_{mit} and various combinations of cointegration between r_{it} and X_{mit} or between r_{it}, X_{mit} and the common factors f_t, as well as noncointegration.

When both N and T are sufficiently large, estimation of panel models can be performed via several alternative approaches, characterised by various degrees of parameter heterogeneity. Classic techniques, such as the pooled and fixed-effects estimators, impose full or a high degree of parameter homogeneity, thus producing inconsistent and misleading results when the coefficients are in fact heterogeneous. To avoid this drawback, the fully heterogeneous-coefficient model imposes no cross-group parameter restrictions and is fitted separately for each group. The mean of the parameters across groups can then be estimated consistently by the simple arithmetic average of the coefficients – this is the Mean Group (MG) estimator developed by Pesaran and Smith (1995).

Though allowing for parameter heterogeneity, the MG approach is based on the hypothesis of cross-section independence, and thus assumes away $\phi_i' f$ or, at best, models these unobservable factors with a linear trend. Thus, as with other standard panel methods, MG estimation leads to inconsistent and biased estimates when cross-section dependence is in fact present in the data. To correct for this drawback, Pesaran (2006) proposes an estimation procedure named 'Common Correlated Effects' (CCE) estimation, which provides consistent estimates in panel data models with a general multifactor error structure. CCE estimation builds upon the intuition that the unobservable common factors f_t can be proxied via cross-sectional averages of the observable variables. Following Pesaran (2006), under the assumption that slope coefficients and regressors are uncorrelated, substituting for u_{it} and averaging (10) across i we have

$$f_t = \bar{\phi}^{-1}\left(\bar{r}_t - \bar{\omega} - \bar{\lambda}'\overline{X}_t - \bar{\varepsilon}_t\right) \tag{13}$$

where $\bar{\phi} = N^{-1}\sum_{i=1}^{N}\phi_i$; $\bar{r}_t = N^{-1}\sum_{i=1}^{N} r_{it}$; $\bar{\omega} = N^{-1}\sum_{i=1}^{N}\omega_i$; $\bar{\lambda} = N^{-1}\sum_{i=1}^{N}\lambda_i$, $\overline{X}_t = N^{-1}\sum_{i=1}^{N} X_{it}$ and $\bar{\varepsilon}_t = N^{-1}\sum_{i=1}^{N}\varepsilon_{it}$. For $N \to \infty$ and $\bar{\phi} \neq 0$, $\bar{\varepsilon}_t = 0$ and cross-sectional correlation can be controlled for via a linear combination of the cross-sectional averages of dependent and independent variables. Modifying the model in (10) accordingly we have

$$r_{it} = \omega_i + \lambda_i' X_{it} + d_{1i}\overline{r}_t + d_{2i}\overline{X}_t + \varepsilon_{it} \tag{14}$$

MG estimation of (14) provides consistent estimates of the model parameters as simple averages of the group-specific estimates, e.g. $\hat{\lambda}_{CCEMG} = N^{-1}\sum_{i=1}^{N}\hat{\lambda}_i$ – this is Common Correlated Effects Mean Group (CCEMG) estimator.[3] Standard CCE estimation does not include a deterministic trend, as this is simply a type of common factor. Nevertheless, the model in (14) can be augmented with a linear trend term to capture idiosyncratic time-varying unobservables evolving linearly over time.

Eberhardt and Teal (2012b) have recently developed an alternative approach, termed Augmented Mean Group (AMG) estimation, which accounts for cross-section dependence by including a 'common dynamic process' in the group regressions. The AMG estimator relies on the following two-stage procedure:

$$\Delta r_{it} = \lambda' \Delta X_{it} + \sum_{t=2}^{T} c_t \Delta D_t + e_{it} \qquad \Rightarrow \hat{c}_t \equiv \hat{\mu}_t^{\bullet} \tag{15}$$

$$r_{it} = \omega_i + \lambda_i' X_{it} + c_i t + d_i \hat{\mu}_t^{\bullet} + e_{it} \tag{16}$$

The first stage is performed via pooled OLS regression of the first-differences model in (15), which is augmented with the $T-1$ year dummies D_t. The coefficients on the (differenced) year dummies, relabelled as $\hat{\mu}_t^{\bullet}$, represent an estimated cross-group average of the evolution of unobservables over

[3] When the individual slope coefficients are homogenous across i, a more efficient estimator can be obtained via pooled estimation of (9), resulting in the Common Correlated Effects Pooled (CCEP) estimator.

time, referred to as the 'common dynamic process'.[4] Intuitively, if f_t is truly common across groups, in each year *t* the coefficient on the year dummy variable D_t in (15) will provide an average estimate of the common factors across groups in that particular year and the inclusion of $T-1$ year dummies produces an estimate (i.e. $\hat{\mu}_t^{\bullet}$) of how the common factors f_t evolve over time. In the second stage (16), the estimated common dynamic process can be imposed on each group member with unit coefficient, by subtracting $\hat{\mu}_t^{\bullet}$ from the dependent variable. Alternatively, the *N* group-specific regressions can be augmented with $\hat{\mu}_t^{\bullet}$ as an explicit variable.[5] As for the MG and CCEMG estimators, the group-specific AMG estimates are averaged across the panel, so that $\hat{\lambda}_{AMG} = N^{-1}\sum_{i=1}^{N}\hat{\lambda}_i$. Each regression model in the AMG setup can also include a linear trend term to capture omitted idiosyncratic processes evolving in a linear fashion over time. The Monte Carlo simulations in Bond and Eberhardt (2009) indicate that inclusion of $\hat{\mu}_t^{\bullet}$ allows for the separate identification of λ_i and the unobserved common factors f_t and g_t.[6]

Both the CCEMG and AMG estimators are sufficiently general to allow for potentially nonstationary and/or nonlinear observables and unobservables, as well as idiosyncratic or global business cycle effects. Thus, we can exploit all the information available in the dataset using annual-data estimation without incurring in the distorting influence normally associated to business cycle components in this type of empirical analysis. Moreover, allowing for heterogeneity in factor

[4] The 'common dynamic process' is extracted from the pooled regression in *first differences* as unobservables (as well as the possible presence of nonstationary variables) would lead to biased estimates in pooled *levels* regressions.

[5] Regarding the issues associated to second stage 'regressions with generated regressors' (Pagan, 1984), Eberhardt and Teal (2012b) point to the theoretical results in Bai and Ng (2008), who show that second stage standard errors need not be adjusted for first stage estimation uncertainty if $\sqrt{T}/N \to 0$, as is arguably the case here. This is supported by simulation results in Bond and Eberhardt (2009), indicating that the average standard error of AMG estimates is of similar magnitude to the empirical standard deviation.

[6] Notice that CCE estimation does not produce explicit estimates for the unobserved factors f_t or factor loadings ϕ_i. The estimated coefficients on the cross-section averaged variables have no meaningful economic interpretation, as these are included solely to purge the bias arising from the presence of unobservable common factors. On the contrary, the AMG approach provides an explicit estimate for f_t, so that the common dynamic process $\hat{\mu}_t^{\bullet}$ is an economically meaningful construct. Indeed, Eberhardt and Teal (2012b) develop the AMG estimator as an alternative to the CCE approach for macro production function estimation, in the context of which $\hat{\mu}_t^{\bullet}$ can be interpreted as common Total Factor Productivity (TFP) evolution over time.

loadings, the CCEMG and AMG estimators can also appropriately account for cross-section dependence associated to spatial correlation and spatial spillovers (Pesaran and Tosetti, 2011; Chudik et al., 2011; Kapetanios et al., 2011). Finally, while the small-sample performance of the AMG and CCEMG approaches is generally broadly similar (Bond and Eberhardt, 2009), the more parsimonious two-stage AMG procedure is likely to outperform the CCE approach in small-sample estimations involving a relatively large number of regressors. As seen, CCE estimation requires inclusion of cross-section averages of all the variables in the model as additional regressors, thus using up more degrees of freedom than the AMG estimator.

3. Data and estimation results

We rely on a slightly unbalanced panel of 52 developed and emerging economies, using annual data over the 1975-2009 years drawn from the IMF International Financial Statistics (IFS) and other sources. Subject to data availability, we choose long-term nominal interest rates on government bonds as our proxy for r_{it}, since these rates are less affected by monetary policy shocks and more by long-term inflation expectations and risk perception. When long-term rates are not available, as in the case of a number of emerging economies, we use (in order of preference) money market rates, savings rates or lending rates.[7] In line with Brito and Bystedt (2010), to avoid undue influence from high-inflation episodes on the results of our analysis, we adopt the following log-transformation for the nominal interest rate: $r_{it}^{\odot} = 100 \times \ln\left(1 + r_{it}/100\right)$. The benchmark 'foreign' interest rate is the 10-year U.S. Treasury bill rate and nominal exchange rate depreciation is measured in terms of units of domestic currency per U.S. dollar. Our sample includes 19 countries which adopted *IT* during the time period under analysis, as well as 33 non-targeters which serve as control group. The dates of *IT* adoption for advanced economies are taken from Ball (2010), while

[7] The order of preference is that adopted by Aisen and Hauner (2008), who also indicate that pooling is not problematic in this case as all the interest rate series used are highly correlated.

for emerging economies we refer to Brito and Bystedt (2010). A detailed description of all the variables and data sources used in this paper, as well as a list of the *IT*-countries, *IT* adoption dates and non-*IT* countries are reported in Tables A1 and A2 in the Appendix.

Table 1. MG estimations and *CD* test

Estimator	MG	MG
Dependent variable	$r_{it}^{\odot}$	$r_{it}^{\odot}$
r_{it}^{*}	1.295**	0.056
e_{it}	0.048**	0.036**
IT_{it}	-1.129^	-1.156**
Linear trend	-	-0.374 **
Intercept	2.611	18.871**
# of country-specific trends significant at 5%	-	26
χ^2 statistic on $H_0 : \hat{\beta} = 1$	0.96	5.63
p-value	0.328	0.018
CD stastistic	40.06	31.93
p-value	0.000	0.000
# of countries	52	52
# of observations	1509	1509

Notes: ** and ^ indicate, respectively, significant at the 1% and 10% level. e_{it} instrumented with first lag.

We start our empirical assessment of the effects of *IT* on nominal interest rates by performing standard MG estimation of the model in (9). The MG results, reported in Table 1, provide clear supportive evidence in favour of the hypothesis that *IT* has significant negative effects on the nominal interest rate: The coefficient on the *IT* dummy is about -1.1 and significant in both specifications. The remaining estimates indicate that the no-trend model results are more in line with the UIP condition. More precisely, while nominal exchange rate depreciation is significant and enters with the expected positive sign in both specifications, only for the no-trend model r_{it}^{*} turns out to be significant too and the null hypothesis that its coefficient is equal to one is not rejected.

Notice, however, that the finding of 26 significant country-specific time trends suggests that the no-trend specification may be misspecified and, more importantly, signals the possible presence of common factors and cross-section dependence. As pointed out, in such a case standard panel methods, such as the MG estimator, break down and yield biased results. Thus, we carry out a formal investigation of this hypothesis making use of a test for cross-section dependence (*CD*) developed by Pesaran (2004).

The *CD* test statistic is based on mean pairwise correlation coefficients for variable series or regression residuals and, in the case of unbalanced panels, is defined as

$$CD = \sqrt{\left(\frac{2}{N\left(N-1\right)}\right)\left(\sum_{i=1}^{N-1}\sum_{j=i+1}^{N}\sqrt{T_{ij}}\,\widehat{\rho}_{ij}\right)} \tag{17}$$

where $\widehat{\rho}_{ij}$ indicates the pairwise correlation coefficients between all country series, while T_{ij} is the number of observations used to estimate the correlation coefficient between the series in countries *i* and *j*. For $T_{ij} > 3$ and sufficiently large *N*, under the null of cross-section independence $CD \sim N\left(0,1\right)$. Moreover, the CD test was shown to perform well in small samples and is robust to parameter heterogeneity, nonstationary processes and/or structural breaks.

Using the residuals from the MG regressions, we carried out the *CD* test for the two specifications in Table 1. As can be seen from the results reported in the table, the null of cross-section independence is strongly rejected in both cases. As mentioned, this outcome implies that standard MG estimation is likely to produce misleading inference. An appropriate estimation strategy should thus control for cross-section dependence, so that we now proceed to the implementation of CCEMG and AMG methods.

Table 2 displays the results from CCEMG and AMG estimation of the model in (9). The *IT* dummy enters with the expected negative sign in five out of the six models considered, but is significant only in three cases. However, the presence of a large number of significant country-specific trends indicates that the three specifications controlling for linear trends are preferable in this case and two of these return significantly negative estimates for *IT*, with coefficients of -0.67 and -0.78.[8] Comparing the two estimators, the AMG approach appears to perform better in relation to the UIP condition. Contrary to the CCEMG alternative, the AMG estimator produces significant estimates for r_{it}^{*} and, in addition, does not reject null hypothesis $H_0 : \hat{\beta} = 1$.

Table 2. CCEMG and AMG estimations

Estimator	CCEMG	CCEMG	AMG	AMG	AMG	AMG
Dependent variable	$r_{it}^{\odot}$	$r_{it}^{\odot}$	$r_{it}^{\odot}$	$r_{it}^{\odot}$	$r_{it}^{\odot} - \hat{\mu}_t^{\bullet}$	$r_{it}^{\odot} - \hat{\mu}_t^{\bullet}$
r_{it}^{*}	0.143	0.012	1.006**	1.083**	1.082**	0.971*
e_{it}	0.031**	0.035**	0.033**	0.030**	0.034**	0.024**
IT_{it}	-0.737*	-0.669*	-0.641	-0.781*	0.124	-0.538
$\hat{\mu}_t^{\bullet}$	-	-	0.893**	1.014**	-	-
Linear trend	-	-0.065	-	0.064	-	0.011
Intercept	1.052	4.479	2.804^	0.755	1.378	2.459
# of country-specific trends significant at 5%	-	13	-	21	-	29
χ^2 statistic on $H_0 : \hat{\beta} = 1$	7.44	7.77	0.00	0.04	0.07	0.01
p-value	0.006	0.005	0.984	0.839	0.787	0.941
# of countries	52	52	52	52	52	52
# of observations	1509	1509	1509	1509	1509	1509

Notes: **, * and ^ indicate, respectively, significant at the 1%, 5% and 10% level. e_{it} instrumented with first lag.

To sum up, the empirical evidence gathered points to significant negative effects of *IT* on nominal interest rates. This outcome is in line with the hypothesis that, by reducing inflation expectations and the risk premium, the adoption of an *IT* regime provides substantial benefits for the conduct of policy.

[8] In the third specification including country-specific trends (last column on the right in Table 2), the *IT* dummy is significant at the 12 percent level.

4. **Robustness of the results**

Recent studies have highlighted some problems with the empirical approaches usually adopted to investigate the effects of *IT* (e.g. Brito and Bystedt, 2010). To address these concerns, in this section we perform a series of robustness checks on the results obtained in Section 3, extending the model formalised in (9) in several respects. Specifically, we consider and deal with the following potential drawbacks in the empirical analysis so far conducted:

1. *IT adoption may be subject to a different type of endogeneity*. The multifactor approach adopted in this paper is well-suited to control for a particular type of variable endogeneity, i.e. that induced by the presence of common factors. However, a number of studies suggest that (at least in some cases) the *IT* regime may be adopted as a policy response to unsatisfactory macroeconomic performance, particularly in terms of average inflation and/or low monetary policy credibility (e.g. Brito and Bystedt, 2010; Lanzafame and Nogueira, 2011). This implies that, at least to a certain degree, *IT* adoption may be endogenous to the nominal interest rate too. That is, countries characterised by high average interest rates may adopt *IT* as a way to anchor inflation expectations and increase monetary policy credibility, thus *ceteris paribus* reducing nominal interest rates. To control for this potential source of endogeneity for *IT*, we augment the model in (9) by including as an additional regressor the average interest rate up to time *t-1*, i.e. $AVr_{it} = \left(\sum_{1}^{t-1} r_{it}\right) \Big/ \left(t-1\right)$;
2. *The degree of central bank independence (CBI) may influence nominal interest rates and the effectiveness of the IT regime*. There is some agreement in the literature that *CBI* improves the credibility of monetary policy, thus helping anchor inflation expectations and reducing nominal interest rates. Moreover, it has been suggested that *CBI* may be a precondition for the successful implementation of an *IT* regime (Mishkin, 2000, 2004; Eichengreen et al., 1999; Friedman and Ötker-Robe, 2010). Thus, there are at least two

possible channels via which the degree of *CBI* may affect the estimates produced by the model formalised in (9). To control for this potential source of misspecification, we include in our estimations the *de jure* index of central bank independence $\left(CBI_{it}\right)$ constructed by Cukierman et al. (1992);

3. *The assumption of a small open economy scenario may not be entirely appropriate*. Our sample includes a large number of emerging economies, which are likely to diverge from the open-economy case in certain respects. We control for this possible deviation from the assumptions at the basis of the UIP condition using the *de jure* index of capital account openness $\left(KAOPEN_{it}\right)$ constructed by Chinn and Ito (2006, 2008);
4. *The estimates may be affected by short-term monetary disequilibrium*. In a less than perfectly open economy, the nominal interest rate will be affected by short-term deviations of the real interest rate from its long-run equilibrium value. These can be brought about by liquidity effects, with excess demand (supply) for real money balances resulting in temporarily higher (lower) real and nominal interest rates. Following Edwards and Khan (1985), we control for this including a proxy for real money supply given by the logarithm of the ratio of money supply to nominal GDP $\left(\log M_{it}\right)$.

In conducting our robustness analysis, we introduce sequentially the control variables AVr_{it}, CBI_{it}, $KAOPEN_{it}$ and $\log M_{it}$, thus gradually extending the model formalised in (9) so that the final specification includes all four.[9] *CD* tests conducted on the residuals from MG estimation of the various versions of the extended model confirmed the significant presence of cross-section dependence.[10] Thus, in what follows we focus on the implementation of the multifactor approaches developed by Pesaran (2006) and Eberhardt and Teal (2012b). The CCEMG estimates are reported in Table 3, while the AMG results are in Tables 4 and 5.

[9] We experimented with different orderings in the sequential introduction of the four control variables, not finding any significant change in the results.
[10] To save space, the MG estimation results and the associated *CD* tests are not reported.

Table 3. CCEMG estimations

Estimator	CCEMG	CCEMG	CCEMG	CCEMG	CCEMG	CCEMG	CCEMG	CCEMG
Dependent variable	$r_{it}^{\odot}$	$r_{it}^{\odot}$	$r_{it}^{\odot}$	$r_{it}^{\odot}$	$r_{it}^{\odot}$	$r_{it}^{\odot}$	$r_{it}^{\odot}$	$r_{it}^{\odot}$
r_{it}^{*}	0.178	-0.041	-0.125	-0.381	-0.232	-0.498	-0.515	-0.098
e_{it}	0.023*	0.028*	0.027*	0.038	0.029	0.022	0.021	0.025
IT_{it}	-0.806**	-0.719^	-0.813*	-0.627	-0.542	-0.690	-0.646	-0.319
AVr_{it}	0.214	0.303	0.220	0.081	0.548	-0.262	-0.002	-2.865
CBI_{it}	-	-	-4.476	-7.571^	-6.486	-7.487	-9.544	1.126
$KAOPEN_{it}$	-	-	-	-	-1.081^	-0.370	-1.124	-1.425*
$\log M_{it}$	-	-	-	-	-	-	-4.069	1.355
Linear trend	-	0.857	-	0.640	-	-0.095	-	0.251
Intercept	-5.818	-96.717	1.394	-51.690	9.541	49.572	40.764	28.680
# of country-specific trends significant at 5%	-	13	-	10	-	9	-	8
χ^2 statistic on $H_0: \hat{\beta}=1$	16.73	34.06	15.80	35.22	34.01	24.10	22.94	24.63
p-value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
# of countries	52	52	50	50	50	50	49	47
# of observations	1485	1485	1420	1420	1394	1394	1289	1271

Notes: **, * and ^ indicate, respectively, significant at the 1%, 5% and 10% level. e_{it} and $\log m_{it}$ instrumented with first lag.

The CCEMG estimates of the coefficient on the *IT* dummy display a negative sign in all the eight models in Table 3, but turn out to be significant only in three cases. Unsurprisingly, this outcome is associated to a general worsening of the performance of the CCEMG estimator as the model is gradually extended to include a greater number of right-hand-side (RHS) variables. The specifications including more than five regressors return very few significant results, as the inclusion of cross-section averages as additional RHS variables weighs heavily on the small-sample performance of the CCEMG estimator. Moreover, as for the CCEMG estimates in Table 2, the null hypothesis $H_0: \hat{\beta}=1$ is always rejected, while the benchmark foreign interest rate r_{it}^{*} is almost always not significant and even enters with a negative sign. Thus, though broadly confirming the role played by *IT* in reducing nominal interest rates, CCEMG estimation does not appear to provide reliable evidence on the overall performance of the extended model adopted in this section.

The more parsimonious AMG estimator performs considerably better. Independently of whether the common dynamic process $\hat{\mu}_t^{\bullet}$ is included as an additional regressor (Table 4) or imposed with unit coefficient on the dependent variable (Table 5), the null hypothesis $H_0 : \hat{\beta} = 1$ is never rejected, the coefficients on r_{it}^* and e_{it} are always significant and, more importantly, the *IT* dummy enters always with a negative sign and turns out to be significant in nearly all specifications considered. If we refer to the specifications including country-specific trends, which again appear to be preferable, the AMG estimates of the negative coefficient on the *IT* dummy are always significant at least at the 5 percent level. Notably, the size of the estimated *IT* coefficients becomes larger as the model is gradually expanded to include all control variables, so that it turns out to be between -0.86 and -1.03 in the four most complete specifications.

As regards the control variables introduced in this section, AVr_{it} enters with the expected positive sign and turns out to be significant in several cases for the results in Table 4, while it is never significant for the AMG estimates in Table 5. The coefficient on CBI_{it} turns out to be always negative indicating that, as expected, greater central bank autonomy reduces interest rates. However, there is only weak evidence that these effects are statistically significant. On the contrary, the *de jure* index of capital account openness appears to perform rather well in controlling for deviations from the open-economy hypothesis. $KAOPEN_{it}$ turns out to be almost always significant (albeit at the 10 percent level in four cases) and, since higher values of the index indicate greater openness, the negative sign on its coefficient is in line with expectations. Finally, $\log M_{it}$ is significant only in one out of the four specifications in which it is included and, puzzlingly, enters always with a positive sign. Note, however, that Aisen and Hauner (2008) obtain the same result and suggest that it may reflect a positive effect of excess money supply on inflation expectations which outweighs the negative liquidity effect.[11]

Table 4. AMG estimations

Estimator	AMG	AMG	AMG	AMG	AMG	AMG	AMG	AMG
Dependent variable	$r_{it}^{\odot}$	$r_{it}^{\odot}$	$r_{it}^{\odot}$	$r_{it}^{\odot}$	$r_{it}^{\odot}$	$r_{it}^{\odot}$	$r_{it}^{\odot}$	$r_{it}^{\odot}$
r_{it}^{*}	1.164**	1.141**	1.173**	1.028**	0.916**	0.861*	1.003**	0.987**
e_{it}	0.023*	0.023**	0.025*	0.023**	0.032*	0.029*	0.029*	0.029*
IT_{it}	-0.539^	-0.857**	-0.639^	-0.866**	-0.697^	-0.838*	-1.030*	-1.024*
AVr_{it}	0.488**	0.384*	0.465**	0.352^	0.266^	0.034	0.194	0.280
CBI_{it}	-	-	-4.193	-4.275	-5.978	-6.400	-3.569	-4.114
$KAOPEN_{it}$	-	-	-	-	-0.546^	-0.616	-0.920*	-0.793^
$\log M_{it}$	-	-	-	-	-	-	4.974	3.386
$\hat{\mu}_t^{\bullet}$	1.119**	1.128**	1.105**	1.056**	1.001**	0.990**	0.939**	0.949**
Linear trend	-	-0.017	-	0.014	-	0.032		0.167^
Intercept	-7.515	1.236	-5.034	1.772	-1.095	3.978	-23.444	-24.074
# of country-specific trends significant at 5%	-	14	-	12	-	12	-	11
χ^2 statistic on $H_0 : \hat{\beta} = 1$	0.16	0.14	0.31	0.01	0.09	0.14	0.00	0.00
p-value	0.693	0.711	0.579	0.940	0.770	0.704	0.994	0.971
# of countries	52	52	50	50	50	50	47	47
# of observations	1485	1485	1420	1420	1394	1394	1271	1271

Notes: **, * and ^ indicate, respectively, significant at the 1%, 5% and 10% level. e_{it} and $\log m_{it}$ instrumented with first lag.

[11] Aisen and Hauner (2008) prefer to use the growth rate of money supply (m_{it}), instead of the level, to control for liquidity effects. We also ran the regressions in Tables 3-5 using m_{it} (rather than $\log M_{it}$) to control for monetary conditions, obtaining very similar results.

Table 5. AMG estimations

Estimator	AMG	AMG	AMG	AMG	AMG	AMG	AMG	AMG
Dependent variable	$r_{it}^{\odot}-\hat{\mu}_t^{\bullet}$	$r_{it}^{\odot}-\hat{\mu}_t^{\bullet}$	$r_{it}^{\odot}-\hat{\mu}_t^{\bullet}$	$r_{it}^{\odot}-\hat{\mu}_t^{\bullet}$	$r_{it}^{\odot}-\hat{\mu}_t^{\bullet}$	$r_{it}^{\odot}-\hat{\mu}_t^{\bullet}$	$r_{it}^{\odot}-\hat{\mu}_t^{\bullet}$	$r_{it}^{\odot}-\hat{\mu}_t^{\bullet}$
r_{it}^{*}	1.249**	0.933**	0.997**	0.855**	0.834**	0.808*	1.129**	0.990**
e_{it}	0.025**	0.019*	0.024*	0.017*	0.031*	0.025*	0.027*	0.022^
IT_{it}	-0.092	-0.735**	-0.415	-0.819*	-0.603^	-0.822*	-0.864*	-1.003*
AVr_{it}	0.074	0.076	0.216	0.119	-0.043	0.124	0.101	0.619
CBI_{it}	-	-	-4.899	-4.934	-8.456^	-9.082^	-6.322	-4.755
$KAOPEN_{it}$	-	-	-	-	-0.619^	-0.607^	-0.953*	-0.847*
$\log M_{it}$	-	-	-	-	-	-	8.595*	5.754
Linear trend	-	-0.120	-	-0.041	-	0.007	-	0.176
Intercept	-5.103^	8.582	-2.295	5.015	4.006	6.847	-34.695^	-34.731
# of country-specific trends significant at 5%	-	24	-	20	-	15	-	14
χ^2 statistic on $H_0:\hat{\beta}=1$	0.59	0.05	0.00	0.20	0.37	0.31	0.17	0.00
p-value	0.444	0.816	0.991	0.658	0.543	0.576	0.676	0.975
# of countries	52	52	50	50	50	50	49	47
# of observations	1485	1485	1420	1420	1394	1394	1289	1271

Notes: **, * and ^ indicate, respectively, significant at the 1%, 5% and 10% level. e_{it} and $\log m_{it}$ instrumented with first lag.

In addition to the estimations presented in this section, we carried out two further robustness checks. First, we estimated the model excluding the Cukierman *de jure CBI* index (CBI_{it}) and introducing an alternative proxy for central bank independence used in the literature, i.e. the turnover rate of central bank governors (TOR_{it}). The turnover rate provides *de facto* information about job security for the central bank governor, so that a higher *TOR* may indicate a lower level of *CBI*. Secondly, we ran dynamic versions of all the model specifications in Tables 3-5, including the first lag of the nominal interest rate as an additional regressor.[12] Both the CCEMG and AMG results from these further estimations turned out to be very similar to their respective counterparts in

[12] We experimented with further lags (up to three) of the nominal interest rate, but these turned out to be not significant in most cases.

Tables 3-5 and, more importantly, the hypothesis that *IT* has a negative impact on nominal interest rates remained largely supported by the data. [13]

Overall, therefore, the robustness checks and sensitivity analysis conducted in this section confirm and, indeed, reinforce the hypothesis that the adoption of an *IT* regime has a significantly negative impact on nominal interest rates.

5. **Concluding remarks**

The implementation of an *IT* regime is commonly considered to be an important strategy to increase monetary policy credibility and improve macroeconomic performance. In particular, a successful *IT* strategy can be expected to bring about lower inflation rates, a fall in inflation volatility and, by decreasing inflation expectations and the risk premium, lead to a structural reduction in nominal interest rates. Focusing on the latter hypothesis, in this paper we build on a risk-adjusted uncovered interest parity framework and use data on 52 emerging and developed economies to investigate the relationship between *IT* and interest rates.

Contrary to previous studies in the field, we adopt a flexible and efficient panel estimation approach, particularly suited to control for parameter heterogeneity and cross-section dependence. Our empirical methodology is based on mean-group estimation and multifactor modelling, making use of the standard mean-group (MG) estimator (Pesaran and Smith, 1995), as well as the multifactor modelling approaches proposed by Pesaran (2006) and Eberhardt and Teal (2012b) – respectively, the 'Common Correlated Effects Mean Group' (CCEMG) estimator and the 'Augmented Mean Group' (AMG) estimator. Our results strongly indicate that *IT* led to a reduction of nominal interest rates in our sample of countries, thus providing qualified support to the hypothesis that this monetary policy framework plays a significantly positive role on interest rate determination. This finding is confirmed by our sensitivity analysis, which conducts several

[13] These additional results are not reported in the paper, but are available upon request.

robustness checks with respect to possible omitted variable bias, as well as endogeneity issues relating to *IT* adoption.

Overall, the evidence gathered in this paper supports the hypothesis that *IT* significantly enhances macroeconomic performance. The outcome of our analysis is of particular interest for emerging markets, which are traditionally characterised by high and volatile interest rates, with detrimental effects on output and employment. For these countries, our results indicate that the adoption of a credible *IT* regime may be an effective monetary policy strategy to boost credibility and help structurally reduce interest rate levels.

Appendix

Table A1. List of variables and data sources

Variable name	*Definition*	*Data sources*
r_{it}	In order of preference: Nominal interest rate on long-term government bonds; money market rate; savings rate; lending rate.	IMF 'International Financial Statistics' (IFS); OECD 'Main Economic Indicators' (MEI).
r_{it}^{*}	Nominal interest rate on 10-year U.S. government bonds.	OECD 'Main Economic Indicators' (MEI).
e_{it}	Nominal exchange rate depreciation, defined in terms of units of domestic currency per U.S. dollar.	IMF 'International Financial Statistics' (IFS).
IT_{it}	Dummy variable equal to 1 for *IT* countries and 0 otherwise.	Ball (2010); Brito and Bystedt (2010).
AVr_{it}	Average nominal interest rate up to year *t-1*, i.e. $AVr_{it}=\left(\sum_{1}^{t-1} r_{it}\right)\Big/(t-1)$.	Authors' calculations using data on r_{it} from IFS and MEI.
CBI_{it}	Cukierman *de jure* index of central bank independence (CBI). The index ranges between 0 and 1, with higher values indicating greater legal CBI.	Constructed by the authors from the following sources: For 1975-1988: Cukierman et al. (1992), with decadal data used for each year of the respective decade; For 1989-2000: Polillo and Guillén (2005), with 2000 value assumed until 2002; For 2003: Crowe and Meade (2008), assumed to persist until 2009.
$KAOPEN_{it}$	*De jure* index of capital account openness. Higher values indicate a higher degree of openness.	Chinn and Ito (2006, 2008).
$\log M_{it}$	In order of preference: Ratio of broad money to GDP; Ratio of M2 (money and quasi money) to GDP.	IMF 'International Financial Statistics' (IFS); World Bank 'World Development Indicators' (WDI).
TOR_{it}	5-year moving average of the number of changes in central bank governors.	Dreher et al. (2008).

Table A2. Country list and dates of *IT* adoption

IT countries	*Date of IT adoption*	*Non-IT countries*
Australia	1995	Algeria, Argentina, Austria, Belgium, Bolivia, China, Costa Rica, Denmark, Dominican Republic, Ecuador, Egypt, El Salvador, France, Germany, Greece, Guatemala, India, Indonesia, Ireland, Italy, Japan, Lebanon, Malaysia, Morocco, Netherlands, Nigeria, Pakistan, Panama, Paraguay, Portugal, Tunisia, Turkey, Uruguay.
Brazil	1999	
Canada	1992	
Chile	1999	
Colombia	1999	
Finland	1994-1998	
Israel	1997	
Mexico	2002	
New Zealand	1991	
Norway	2001	
Peru	2002	
Philippines	2002	
South Korea	1998	
South Africa	2000	
Spain	1995-1998	
Sweden	1995	
Switzerland	2000	
Thailand	2000	
United Kingdom	1993	

Notes: Dates of *IT* adoption taken from Ball (2010) and Brito and Bystedt (2010); Finland and Spain abandoned the *IT* regime at the end of 1998 because of the advent of the Euro.

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