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Refining natural interest rate estimation for India

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ABSTRACT

Natural interest rates (NIRs) are expected to exceed those in advanced economies in emerging market economies (EMEs) because their higher growth is thought to require more savings. But the mature economy homogeneous agent models in which the real interest rate equilibrates savings to investment are inappropriate. Aggregate savings rise with income, as productivity and employment expand, while rates of interest largely affect allocation of savings and investment. The latter is often the real constraint. The Reserve Bank's official estimation of the NIR follows the standard framework and finds the NIR to rise with growth. We replicate their method, for a more recent dataset, and use it as a benchmark to see how the estimated NIR varies when features relevant for EMEs are modelled. The first variant introduces the dualistic structure of the economy, with pervasive informality and still large numbers employed in agriculture. The second has an alternative data-based decomposition of the trend from the cycle. The third uses one year ahead realized inflation as a proxy for expected inflation, since using the past trend misses the impact of inaccurate forecasts on the real interest rate. We also try alternative priors. In each case we find the estimated NIR is lower than in the benchmark, which itself is about unity for 2024, compared to the official estimate of 1.4-1.9. Allowing correlation between the cycle and the trend, which is a feature of EME growth, lowers the NIR substantially.

Keywords: Natural interest rate, emerging market economy, dualism, India

JEL Code: E52, E43, E32

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Abstract

Natural interest rates (NIRs) are expected to exceed those in advanced economies in emerging market economies (EMEs) because their higher growth is thought to require more savings. But the mature economy homogeneous agent models in which the real interest rate equilibrates savings to investment are inappropriate. Aggregate savings rise with income, as productivity and employment expand, while rates of interest largely affect allocation of savings and investment. The latter is often the real constraint. The Reserve Bank's official estimation of the NIR follows the standard framework and finds the NIR to rise with growth. We replicate their method, for a more recent dataset, and use it as a benchmark to see how the estimated NIR varies when features relevant for EMEs are modelled. The first variant introduces the dualistic structure of the economy, with pervasive informality and still large numbers employed in agriculture. The second has an alternative data-based decomposition of the trend from the cycle. The third uses one year ahead realized inflation as a proxy for expected inflation, since using the past trend misses the impact of inaccurate forecasts on the real interest rate. We also try alternative priors. In each case we find the estimated NIR is lower than in the benchmark, which itself is about unity for 2024, compared to the official estimate of 1.4-1.9. Allowing correlation between the cycle and the trend, which is a feature of EME growth, lowers the NIR substantially.

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1. Introduction

Since many central banks now follow an inflation targeting regime with the policy rate as the major operating instrument, there is a focus on the natural interest rate (NIR) both from the research and practice point of view. The NIR is the neutral real interest rate at which monetary policy is neither accommodative nor contractionary, so that inflation is stable near the targeted value and output is near potential. Since there is neither an inflationary nor a deflationary gap, it therefore offers a benchmark for judging policy. The problem is that it is not an observable and has to be estimated or inferred from the data.

Just as the practice of inflation targeting came to emerging market economies (EMEs) from advanced economies (AEs) the understanding of the basic determinants of the NIR has also come from AEs to EMEs. As the marginal productivity of capital rises, consumers are thought to require a higher interest rate in order to save more. That is, the natural rate balances the demand for (investment) with the supply of savings.

Empirical work for AEs has documented a fall in the NIR as a result of the so called savings glut, due largely to income inequality, demographic change and a slowdown in productivity growth. All these tend to raise savings and reduce investment[1]. After the pandemic, however, rising public debt has acted as a counteracting force increasing NIR, although the factors reducing NIR are expected to dominate again. Open economy effects largely cancel out since although capital flows to EMEs should be raising AE NIRs, much of the capital returns as EMEs accumulate reserves and invest in AE government treasuries.

AE real interest rates fell by about 5% since the 1980s. EME real rates were converging to AE rates in the 2000s, but stayed at 2005 levels after 2011, while AE rates became negative (IMF 2023).

EME NIRs are thought to exceed AE NIRs because of higher marginal productivity of capital and growth, requiring more savings, risk factors such as higher government debt and others that raise volatility and risk premia. Even so, they are expected to converge to AE levels over time.

There are several issues with this view, however. First, household savings tend to be higher in EMEs. At the aggregate level it is often investment that is the real constraint, which requires lower real interest rates. An indicator of this is the EME savings invested in AE government treasuries.

Second, the mature economy homogeneous agent models in which the real interest rate equilibrates savings to investment are inappropriate. Aggregate savings rise with income, as higher productivity employment expands, while rates of interest largely affect allocation of savings.

[1] The literature is surveyed in IMF (2023) Chapter 2. Empirical work in the chapter is largely based on Platzer and Peruffo (2022) who, using a heterogeneous agent, overlapping generation model, go into great detail on the impact of tax-social security systems on the incentives to save. Even holding inequality constant, households becoming richer due to total factor productivity growth is the major cause of falling NIR.

There are factors reducing EME NIRs. Goyal (2009) finds in an optimizing model of a small open emerging market economy with dualistic labour markets and two types of consumers, changes to subsistence consumption have the largest effect on the NIR, tending to lower it unless wages are rising with inflation (Goyal and Arora, 2016), while technology and infrastructure backwardness raise NIR. The factors lowering NIR dominated for India. Lower rates support the required income growth.

Third, transitional growth and potential output can be higher in EMEs, if policies address structural bottlenecks and labour productivity rises. But actual growth remains more volatile because of external shocks and pro-cyclical macroeconomic policies that aggravate shocks, since they imply that the real rate deviates often from the natural rate. Reducing these deviations is required to smooth growth.

The RBI follows the typical AE framework in official estimation of the NIR, while emphasizing the problems in estimation and the wide error bands that should therefore hedge any estimate. Pattanaik et al (2022) estimated the NIR had fallen after the pandemic to around unity, echoing global trends, while a re-estimate (Behera, 2024) found it had risen again, to a range of 1.4 to 1.9, largely because growth had risen.

The method the above studies follow is the canonical Laubach and Williams (2003) (LW, henceforth) semi-structural method with Bayesian estimation. In this paper we replicate their method, for a more recent dataset. The NIR we estimate is around unity for 2024. But our main aim is to use this estimation as a benchmark and see how the estimated NIR varies when features relevant for EMEs are brought in.

Therefore, we estimate model variants to address the issues affecting EME NIRs outlined above. The first structural variant introduces the dualistic structure of the economy, with pervasive informality and still large numbers employed in agriculture. For robustness alternative measures of dualism are used.

Second, there are many unresolved issues in decomposition of the trend from the cycle, and this is especially so for EMEs. In the second statistical variant, we use an alternative data-based decomposition without imposing any priors. In each of the above cases we find the estimated natural rate is lower.

In the absence of adequate data on inflation expectations the RBI estimates, use past trend inflation to estimate inflation expectations. IT has to be forward-looking and inflation forecasts play an important part in its implementation. But the frequent supply-shocks EMEs are subject to often lead to forecast errors that affect real interest rates. The trend estimate does not capture this short-term volatility. Past trend forecasts may also miss changes in the structure of inflation. Therefore, to conduct sensitivity analysis to understand these effects, we also estimate a third variant using one year ahead realized inflation as a proxy for expected inflation. The estimated NIR differs slightly but is again below unity for the 2020s.

The rest of the paper is organised as follows. Section 2 brings out the contrast between AE and EME estimation of the NIR in the literature. Section 3 presents some relevant stylized facts for India. Section 4 covers the methodology and data. Section 5 has analysis of the results before Section 6 concludes with policy implications.

2. Comparing NIR in advanced and emerging economies

IMF (2023), using a detailed structural model, finds the major factors reducing NIRs in AEs are total factor productivity growth and demographic forces. The first reduced the returns to capital and the second increased savings. Other factors such as net capital inflows, increase in inequality or lower labor shares also contributed, while rising government debt tended to raise the NIR. But these factors had a smaller impact. If government debt continues to rise, however, convenience yields may fall and risk premia rise, raising NIRs. They see taxes and regulations in the transition to a green economy reducing the marginal productivity of capital and lowering global NIRs, but deficit-financing of green investment could counter this.

Their projections of future demographic and productivity trends suggest a gradual fall in NIR's of large EMEs towards AE levels. India's NIR is estimated at 2 and expected to fall to 1 by 2035. IMF (2015) using quarterly data from 2008: Q4 to 2014: Q3 had earlier estimated the NIR to be 1.3 per cent in 2001-08 and 1.1 per cent in 2009-14[2].

FIs raise capital productivity and therefore EME natural rates, but since their financial markets are underdeveloped, EMEs own savings are reinvested in AE government securities so the net effect of global forces on the NIR is limited. Obstfeld (2020) also brings out opposing effects of capital flows. He argues NIR falls for a country with a current account deficit if there is a global current account surplus; while real exchange effects on real interest rates through interest rate arbitrage are temporary, gross capital flows can create risks in specific financial sectors. Overall, since own savings dominate in EMEs, if deglobalization intensifies the NIR would tend to rise in AEs and fall in EMEs (IMF, 2023).

3. Stylized facts relevant for the Indian NIR

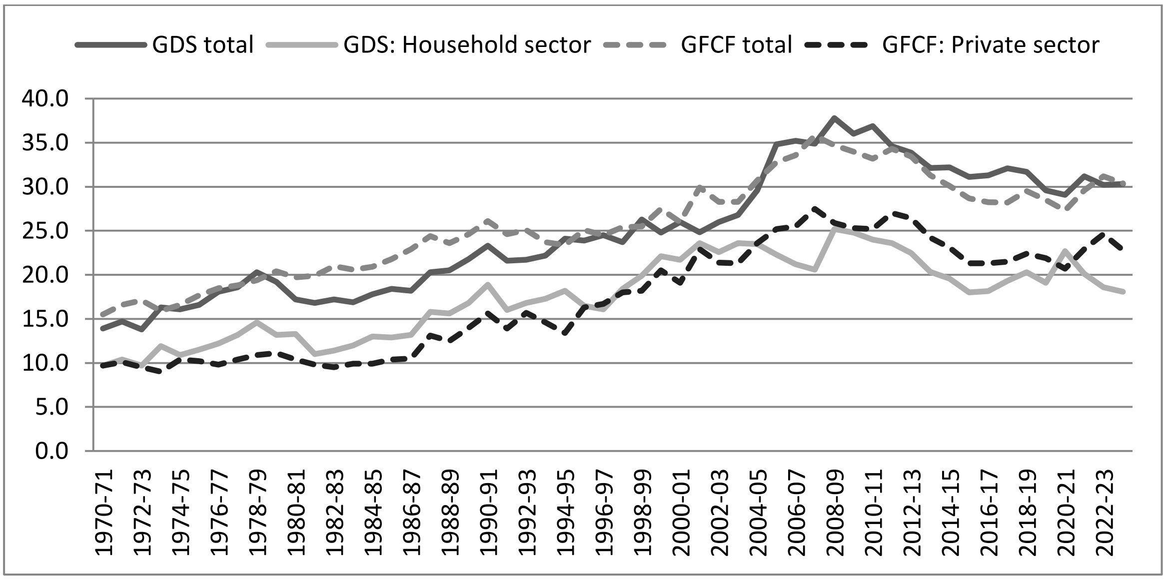
The literature reviewed above indicates that the NIR rises when savings fall relatively, or the demand for resources exceeds their supply. But Indian data suggests savings follow a rise in investment- driven growth. A rise in demand induces supply-response.

After independence, Indian savings as a percentage of Gross Domestic Product (GDP) tend to fall in low growth periods and rise when growth is high, although financial sector development also affects savings. Expansion and better spread of branches after bank nationalization led to a peak in the seventies rate to about 20%, but it fell with stagflation and lower public sector savings as the government began to borrow even for revenue expenditure.

[2] This was in a semi-structural estimation with an extended Taylor-rule, the estimated values ranged from 5.4 to 2.6 with other methods.

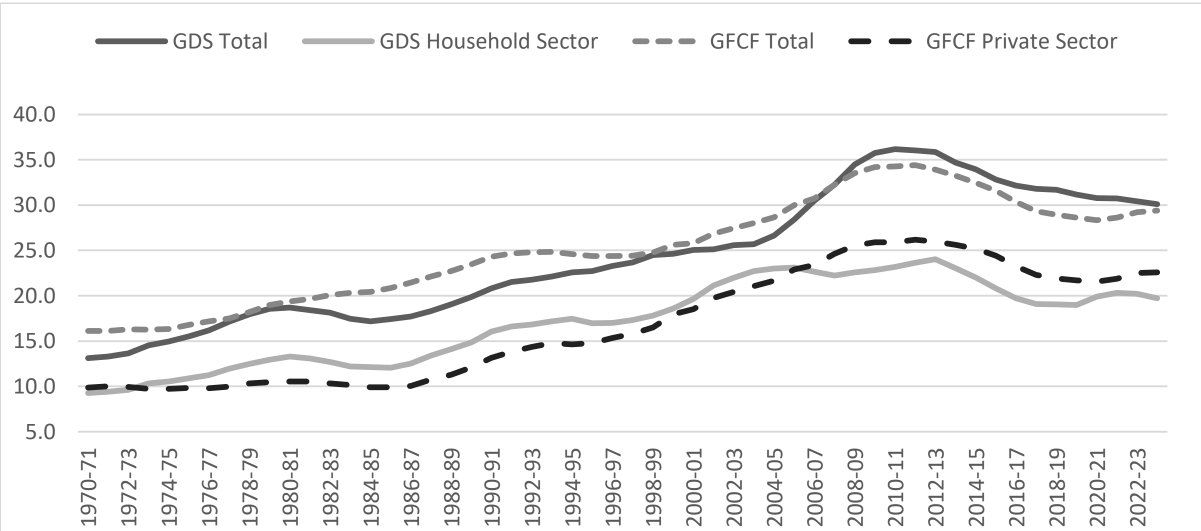
After a low of 17% in the mid-eighties, it recovered to peak at 23.2% 1978/79. As it stagnated below this peak after liberalizing reforms in the early 1990s, there were fears that the fall in savings would hamper growth. But the mid-90s growth spurt raised the ratio above 25%, and that in the 2000s substantially raised savings: In 2008-09 the ratio peaked at 37.8. This pattern continued—the savings ratio fell as growth softened in the 2010s but rose with the post-pandemic growth recovery to about 30%, but now household savings were lower by about 7%, which had shifted to increasingly cash-rich corporates.

Figure 1: Time series of savings and investment and their components



Source: Calculated from Economic survey data https://www.indiabudget.gov.in/economicsurvey/

Figure 2: Moving averages of the savings and investment series



Source: Calculated from Economic survey data https://www.indiabudget.gov.in/economicsurvey/

Turning points in Gross Fixed Capital Formation (GFCF) normally led those in savings (Figure 1); suggesting that growth was investment, not savings led. Savings rose, flattened and fell as GFCF raised jobs and incomes. Although it is a macroeconomic identity that savings must equal investment, GFCF and gross savings are not identical since they are measured by different methods. But components also show the same structure of movement. That private GFCF now exceeds household sector savings shows that while the corporate sector drew on household savings earlier, in recent years it can also draw on own surpluses. The trends show more clearly in 5 year moving averages (Figure 2).

Table 1: Ex-post real interest rates and growth

	Call money rate (CMR)	Inflation: WPI	Inflation: Headline CPI	Real CMR (CMR-WPI)	Real CMR (CMR-Hdl CPI)	Real GDP growth
1970-71 to 1979-80	8.6	9.4	7.7	-0.8	0.9	2.9
1980-81 to 1989-90	9.4	8.0	9.1	1.4	0.3	5.6
1990-91 to 1999-00	11.5	8.1	9.5	3.4	2.0	5.8
2000-01 to 2009-10	6.1	5.4	5.9	0.7	0.2	6.3
2010-11 to 2019-20	6.9	3.9	6.6	3.0	0.3	6.6
2011-12 to 2013-14	8.2	7.0	9.5	1.2	-1.3	5.7
2017-18 to 2019-20	5.9	3.0	3.9	2.9	2.0	5.7
2020-21 to 2024-25	5.0	4.9	5.5	0.1	-0.5	5.4
2020-21	3.4	1.3	6.2	2.1	-2.7	-5.8
2021-22	3.3	13.0	5.5	-9.7	-2.3	9.7
2022-23	5.4	9.6	6.7	-4.2	-1.2	7.6
2023-24	6.5	-0.7	5.4	7.2	1.2	7.2
2024-25	6.5	2.3	4.6	4.2	1.9	7.1

Source: Calculated from RBI database www.rbi.org.
Note: CPI-IW is used before 2012-13; growth rates from 2022-23 are from the revised 2022-23 base series; the prior base is 2011-12

Prior to a model and data-based estimation of the NIR, it is useful to look at the relationship between ex-post real short-term rates, inflation and growth. If a higher real interest rate raised savings and therefore growth, ex-post higher real interest rates should accompany higher growth. But Table 1 shows the reverse.

The short rate given in the Table is the call money rate (CMR), or inter-bank overnight borrowing rate, since the repo rate was not used in the 1970s but the CMR was an operational target even then. Flexible inflation targeting (FIT) was only adopted in the mid-2010s.

Since the nineties, in periods of relatively lower growth, real interest rates derived from CPI headline (CPI-IW prior to 2013-14) have exceeded 1.5. Two of these periods (2017-18 to

2019-20 and 2024-25[3]) are in the FIT period. While many factors affect these variables, the stylized facts do not suggest that higher real interest rates accompany higher growth. Excess tightening episodes that raised real rates above unity have occurred prior to FIT, such as in the 1990s.

But there were also episodes where low real interest rates accompanied low growth. For example, high double-digit inflation, as in the 1970s and in the early 2010s resulted in low growth despite low real interest rates. Rigorous analysis is required to extract causality and equilibrium values.

High real interest rates in terms of WPI do not show the same negative impact since they are normally associated with a fall in fuel oil prices that benefits consumers and firms.

4. Methodology

Behera (2024) covers the various estimation methods used in the literature. The method used following Pattanaik et al. (2021) is the semi-structural LW, which combines a Ramsey growth model with a New Keynesian (NK) aggregate demand (or investment equals savings, IS) and aggregate supply or Phillips curve.

The Ramsey model assumes that potential growth is determined by savings. The latter is affected by the real interest rate in excess of the rate of time preference depending on the intertemporal elasticity of substitution. LW generalize this to make the NIR a function of its own lags, the potential growth rate and other low frequency structural shocks z that are assumed to follow a random walk. These capture determinants other than the growth rate, but do not include transitory demand and supply shocks, since the NIR is the level of the real interest at which growth is at potential and inflation is at target if wages and prices are perfectly flexible and short-run shocks have passed. It is also the level where savings equal investment. If savings fell short, there would be over-heating, and rates have to rise to raise savings relative to consumer time preferences

The output gap (in the IS) is affected by the difference in the policy rate from the NIR and a Taylor rule adjusts the policy rate to close inflation and output gaps, raising rates if inflation exceeds target and output exceeds potential and reducing them if the gaps are negative. Positive inflation and output gaps imply real rates are below the neutral rate.

Thus, LW is semi-structural since it estimates NIR from consumer preferences affecting savings and growth as well as other semi-structural longer-run factors. Short-run shocks cause output to deviate from potential.

[3] Under the old GDP series growth fell from 9.2 to 6.5 but in the new series although the fall was only from 7.2 to 7.1, growth of interest sensitive components such as manufacturing fell from 12.3 to 9.7, construction from 9.9 to 7.3, tertiary sector 10.1 to 6.6, consumption stagnated at 5.8%, while GFCF fell from 7.3 to 6.4. But a rise in agriculture and mining growth protected overall GDP growth. The new series picks up more of the diversity in India’s development, which itself tends to reduce growth fluctuations.

NIR, potential output and its growth are unobservables, assumed to follow a certain law of motion, so state space modeling is required. These state variables must be estimated consistently with observed variables. As Pattanaik et. al argue, Bayesian estimation with loose priors generates more reliable estimates compared to maximum likelihood estimates for the LW model. We explain the methodology used first for the baseline LW model, then for the variants we estimate.

4.1 LW state space model

As in LW, we specify an 8-dimensional linear Gaussian state-space model.

State vector

The state vector is:

$$s_t = \begin{pmatrix} x_t \\ x_{t-1} \\ y_t^* \\ g_t \\ \mu_t \\ r_t^* \\ \xi_t \\ z_t \end{pmatrix}$$

where $x_t$is the output gap, y_t^* is potential (trend) output, g_t is trend growth, μ_t is trend inflation, r_t^* is the natural rate of interest, ξ_t is the inflation gap, and $z_t$is an auxiliary factor driving r_t^*.

Measurement equations

These link the unobserved states to the observed data:

$y_t = y_t^* + x_t + v_t^y$ (Real GDP decomposition)

$\pi_t = \mu_t + \xi_t + \nu_t^\pi$ (Inflation decomposition)

The terms ν_t^y and ν_t^π are measurement errors, assumed to be normally distributed with mean zero and variances σ_y^2 and σ_π^2 , respectively.

Transition equations

The following transition or state equations govern the dynamics or laws of motion of unobserved states:

Output Gap (IS curve):

$x_t = (y_t - y_t^*) = \phi_1 x_{t-1} - \phi_2 x_{t-2} - \gamma_1(r_{t-1}^{real} - r_{t-1}^*) + \epsilon_t^x$----------------(1)

Potential output evolves as local level with drift:

$y_t^* = y_{t-1}^* + g_{t-1} + \epsilon_t^{y^*}$ ---------------------------(2)

Trend growth:

$g_t = g_{t-1} + \epsilon_t^g$---------------------------(3)

Trend inflation:

$\mu_t = \mu_{t-1} + \epsilon_t^{\mu}$--------------------(4)

Natural rate of interest (NIR):

$r_t^* = \rho_r r_{t-1}^* + (1 - \rho_r)\left(\theta_g g_t + z_t\right) + \epsilon_t^r$-------------------(5)

The parameter ρ_r governs the persistence of the NIR, while θ_g measures its sensitivity to trend growth and depends on the intertemporal elasticity of substitution.

Other medium run determinants of NIR, such as preference shocks, are captured by z_t. In these models, shocks to NIR affect the optimal output gap.

$z_t = z_{t-1} + \epsilon_t^z$-----------------(6)

Inflation gap, ξ_t, (Phillips curve):

$\xi_t = (\pi_t - \mu_t) = b_1 x_{t-1} + b_2 x_{t-2} + \epsilon_t^{\xi}$----------------------(7)

The innovation terms ϵ_t^{ξ} are assumed to be serially uncorrelated and normally distributed with their own variances (e.g. for equations 2 and 3, σ_x^2, σ_g^2).

The model incorporates a Taylor-type rule for the nominal interest rate:

$i_t = \beta_9 i_{t-1} + (1 - \beta_9)\left[r_t^* + (1 - \beta_{10})\mu_t + \beta_{11} x_t + \beta_{10} \pi_t^{yoy}\right] + \epsilon_t^i$----------------------(8)

The model is estimated in a Bayesian framework. Persistence parameters are assigned beta priors. Taylor rule coefficients follow normal priors. Variance parameters are given as gamma priors.

Estimation is carried out via a Metropolis–Hastings sampler with 50,000 iterations with 50% burn in, discarding the first half as burn-in. Each proposal runs the Kalman Filter and evaluates the posterior density, while inadmissible draws are rejected. Posterior medians and credible intervals are reported, and the smoothed states yield estimates of potential output y_t^*, the output gap x_t, trend inflation μ_t, and the natural rate of interest r_t^*.

LW dual

In the Ramsey model in the steady-state real interest rate equals the consumer time discount rate plus the population growth rate. But catch-up growth exceeds the growth rate of population. NIR has to rise with growth to raise savings to finance growth. But in the dual economy model (Goyal, 2009) there are additional shocks affect both potential output and NIR.

Subsistence consumption and the gap from world income levels, tend to raise potential output while technology and infrastructure backwardness reduce it. The gap signifies the role of catch-up in raising potential output. As catch-up progresses, improvements in technology and infrastructure will raise potential output while a rise in subsistence consumption levels towards global averages would lower it. Shocks that raise potential output lower the NIR. While the semi-structural LW model looks through short-run demand and supply shocks to smooth NIR, structural changes affect it.

When consumption of the poor is below world consumption, C*, normalized at unity, this raises the potential output since underdevelopment signifies an unrealized potential. As development occurs, with less productive labour absorbed into the modern sector, consumption and other coefficients approach world levels.

Policy has to take account of structural changes in NIR, in order to accommodate rather than choke changes in potential output. The higher output raises savings to finance growth. If policy makers do not allow for rising potential output they raise interest rates with output although the output gap is unchanged.

Therefore, in the LW framework, we add shocks to the natural rate equation to account for the effects of dualism. Structural demographic factors are used to proxy for this. These are the relevant demographic forces in an EM equivalent to those found dominant for AEs in the IMF (2023) structural NIR estimation.

Specifically, Equation (5) is adjusted to include the share of the rural population (D_t) as an influencing variable:

$$r_t^* = \rho_r r_{t-1}^* + (1-\rho_r)\left(\theta_g g_t + z_t - \alpha_D(D_t)\right) + \epsilon_t^r$$

The Economic Survey (2023) gives 65% as the approximate share of rural areas in India’s total population. Development is accompanied by migration to higher productivity jobs. The coefficient $\alpha_D(D_t)$ captures the effect of the ongoing demographic transition in reducing the NIR. Lower real interest-rates help absorb labour in productive sectors.

Since food inflation has a large impact on subsistence consumption, Goyal and Arora (2016) added it to the NIR equation as a proxy for short-run shocks to subsistence consumption.

Here we are interested in more structural longer-run changes. LW point out using structural features compensates for some of the data weaknesses and can improve NIR estimation. They use data on hours worked to increase the precision of potential output estimates.

In addition, we use share of rural workforce, agricultural employment share and informal employment share for robustness as alternative structural variables affecting NIR.

LW realized inflation

In a second variant of the baseline LW framework, for sensitivity analysis, trend inflation $\mu_t$is replaced by a proxy for expected inflation constructed as four-quarter-ahead CPI inflation. This is our realized inflation LW specification. This is volatile and not a measure of actual inflation expectations, but fits the aim of assessing the effect on the real interest rate of inflation forecast errors. Forecasts play a major role in policy rate setting under inflation targeting, but errors are frequent in EMEs because of the large share of volatile food inflation in the headline inflation target.

$$\pi_t^{tf4} = 100(logCPI_{t+4} - logCPI_t)$$

This proxy enters the Phillips Curve and the Taylor rule in place of the latent trend inflation state used earlier, while the remaining state-space equations and priors remain identical to the LW baseline.

The model is estimated using the same Bayesian Metropolis–Hastings procedure, and smoothed states provide estimates of the output gap, potential output and the natural rate of interest under the realized-inflation expectation measure.

Beveridge-Nelson (BN) decomposition

Research suggests that the cycle affects the trend in EMEs and has persistent effects on growth. Decomposition of output into trend (permanent) and cycle (temporary) components is not a settled issue. There is no neat separation between the short- and the long-run.

Blanchard and Quah (1989) use a bivariate VAR of real output growth and the unemployment rate to decompose real output into its temporary and permanent components. They interpret the disturbances that have a temporary effect on output as being mostly demand disturbances and those that have a permanent effect on output as mostly supply disturbances. But they acknowledge that unemployment might in fact be nonstationary with long run effects from demand and supply disturbances, as in models with sticky or "hysteresis" effects on unemployment or in growth models with increasing returns to scale, where savings rate changes affect the growth rate of output as well as the level. These kinds of persistent effects are especially relevant for EMEs. Aguiar and Gopinath (2007) find 'the cycle is the trend' for EMEs.

Indian macroeconomic structure can be characterized as a relatively flat supply curve subject to shocks. This implies a positive correlation between cycle and trend shocks, as policy contracts demand in response to supply shocks. There is evidence of such a structure and correlation[4].

Extracting unobservables is influenced by statistical techniques used. For robustness and sensitivity analysis, we also implement a decomposition proposed by Beveridge and Nelson in 1981, following the state-space approach of Basistha and Nelson (2007) (BN). This provides a model-free, statistical estimate of trend and cycle. The time-series model lets the data identify a stochastic trend component, a long horizon forecast with a unit root.

$Y_t = P_t + x_t + \nu_t^y$ (Log GDP equals permanent component plus gap)

$\pi_t = \widetilde{\pi_t} + \delta x_t + \nu_t^{\pi}$ (Inflation equals trend inflation plus gap effect)

The state transitions are:

Permanent component:
$P_t = P_{t-1} + \mu + \epsilon_t^P$ ----------------------------(9)

Where μ denotes a constant drift term capturing the long-run average growth rate of potential output and ϵ_t^P is an innovation to the permanent component.

Output gap (x_t):
$x_t = \phi_1 x_{t-1} + \phi_2 x_{t-2} + \epsilon_t^x$------------------(10)

Trend inflation:
$\widetilde{\pi_t} = b_0 + b_1 \pi_t^e + b_2 \pi_t^{yoy} + \epsilon_t^{\pi}$-------------------------(11)

Following BN (2007), we impose the long-run neutrality restriction $b_1 + b_2 = 1$, which ensures that inflation expectations and lagged inflation jointly account for unit persistence in the trend component. In our implementation, inflation expectations π_t^e, is proxied by lagged year-on-year inflation.

Using smoothed posterior medians for states, we construct time series for $r_{t,}^*(natural\ rate\ proxy)$, x_t $(output\ gap)$, $\xi_t(inflation\ gap)$ and estimate the IS curve, Phillips curve and Taylor rule via classical regressions with Newey–West standard errors to account for heteroskedasticity and autocorrelation.

[4] See: Goyal and Kumar (2018), Goyal and Goel (2019) and Goyal and Ray (2025). The latter in extensive tests find a flat AS with frequent supply shocks that reduce demand fit the data best. Thus demand and supply shocks are correlated. Goyal and Goel (2019) explore decomposition between trend and cycle on the basis of different model parameters.

Finally, the NIR is obtained as a function of its lagged value, the permanent component of output and other structural shocks z_t. The estimating transition equation is:

$$r_t^* = \rho_r r_{t-1}^* + (1 - \rho_r)\left(\theta_p P_t + z_t\right) + \varepsilon_t^r \quad \text{---------------------} \qquad (12)$$

This differs from (5) in that the P_t, the permanent component of output, replaces trend growth and θ_p measures the sensitivity of NIR to movements in potential output.

4.2 Data

The analysis uses quarterly Indian macroeconomic data from 1999Q1 to 2024Q4, base 2011-12, covering real GDP (in INR crores, seasonally adjusted and log-transformed and denoted as y_{obs}), the Consumer Price Index (CPI, seasonally adjusted and log-transformed), and the 91-day Treasury bill yield as the short-term nominal interest rate (i_t). Real GDP data are obtained from the National Statistical Office (NSO), while CPI-Combined and 91-day Treasury bill yield data are sourced from the Reserve Bank of India Database on Indian Economy (DBIE).

From these series, we construct quarter-on-quarter annualised inflation (π_{qoq})as a four-quarter moving average of annualised CPI growth, year-on-year inflation (π_{yoy}) and the real interest rate $r_{real} = i_t - \mu_t$. All dates are converted into quarterly indices, and missing values are omitted to ensure consistency in estimation. Table 2a gives the summary statistics of the data used in the estimations. It shows large variation in the variables. In Table 2b the cross-correlations have the expected signs.

Table 2a: Summary statistics

Variable	Mean	SD	Min	Max	Skew	Kurt	Obs.
Log_GDP	6.336	0.21	5.981	6.68	-0.176	-1.247	101
Log_CPI	1.97	0.207	1.65	2.29	0.095	-1.44	101
π_yoy	5.858	3.503	-2.916	18.495	1.546	3.674	101
$\mathbf{i_t}$	6.407	1.708	3.038	10.004	-0.157	-0.663	101
$\boldsymbol{\mu_t}$	5.845	2.076	3.387	11.622	1.145	0.547	101
$\mathbf{r_{real}}$	0.552	2.758	-7.77	6.305	-1.09	1.981	100

Source: Estimated by authors

Table 2b: Cross-correlations

Lag	output-inflation (y_{obs}, π_{yoy})	Output-interest rate (y_{obs}, i_t)	Inflation -interest rate (π_{yoy}, i_t)
-4	0.082	-0.212	-0.045
-3	0.069	-0.199	-0.106
-2	0.061	-0.188	-0.152
-1	0.045	-0.179	-0.142
0	0.035	-0.170	-0.162
1	0.009	-0.139	-0.104
2	-0.004	-0.114	-0.050
3	-0.010	-0.100	-0.010
4	-0.016	-0.081	0.067

Source: Estimated by author

5. Results

We present and analyse the results for our baseline LW framework and other variants estimated.

5.1 LW framework

The Bayesian estimation of the Laubach–Williams style model for India over 1999Q4–2024Q4 indicates a highly persistent macroeconomic structure, with past output gaps and deviations of the real interest rate significantly influencing current output, and the output gap moderately affecting inflation through the Phillips curve.

The Taylor rule parameters show that monetary policy is highly inertial, responding systematically to both inflation and the output gap, while the NIR evolves gradually in line with trend growth and structural factors (Table 3).

Overall, the results reflect the slow-moving but stable dynamics of the Indian economy, and the Metropolis–Hastings sampler achieved an acceptance rate of 0.21, ensuring reliable posterior estimates.

The estimation differed from the RBI studies only in a longer time period and in not correcting GDP for the Covid year 2020[5]. The coefficient estimates imply a smaller net impact of the output gap on aggregate demand and a larger interest elasticity of demand. Other coefficients are similar. The slope of the AS remains low.

[5] This was tried but the coefficients were similar since by now a number of years have gone by. Moreover, the policy response to the shock needs to be included in the estimations.

Our estimated r* averages 0.84 in 2024 compared to the Behera (2024) upward revision to 1.4% from 1% post pandemic and 2% pre-pandemic. Our average is 0.53 for the pandemic year 2020 and unity before that.

Table 3a: Parameters estimates for LW and LW with reduced priors

Equations	Parameters	Variables	LW Prior mean	LW Prior s.d.	LW Posterior mean	LW Posterior s.d.	LW (reduced prior) Prior mean	LW (reduced prior) Prior s.d.	LW (reduced prior) Posterior mean	LW (reduced prior) Posterior s.d.
	ϕ_1	$(y_{t-1} - y_{t-1}*)$	0.6	0.15	0.616	0.146	0.3	0.15	0.289	0.136
IS curve	ϕ_2	$(y_{t-2} - y_{t-2}*)$	0.3	0.15	0.55	0.181	0.15	0.15	0.165	0.115
	γ_1	$(r_{t-1} - r_{t-1}*)$	0.3	0.15	0.318	0.147	0.15	0.15	0.157	0.120
Phillips curve	b_1	$(y_t - y_t*)$	0.13	0.05	0.146	0.081	0.13	0.05	0.141	0.081
	b_2	$(y_{t-1} - y_{t-1}*)$	0.11	0.05	0.136	0.075	0.11	0.05	0.11	0.069
	β_9	i_{t-1}	0.8	0.19	0.976	0.011	0.8	0.19	0.976	0.011
Taylor rule	β_{10}	$(\pi^{yoy}{}_t - \mu_t)$	1.5	0.1	1.498	0.109	1.5	0.1	1.478	0.099
	β_{11}	x_t	0.3	0.07	0.297	0.073	0.3	0.07	0.299	0.049
Natural rate	ρ_r	$r_{t-1}*$	0.95	0.025	0.953	0.032	0.47	0.025	0.459	0.139

Source: Estimated by authors

Table 3b: Parameters estimates for LW dual model

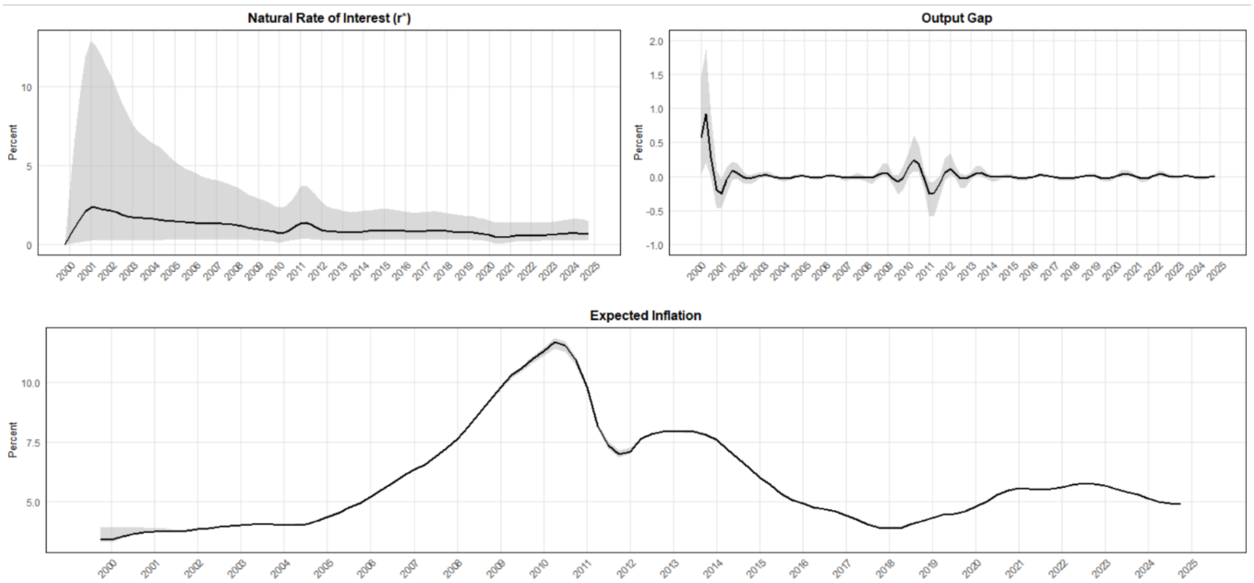
Equations	Parameters	Variables	LW dual Prior mean	Prior s.d.	Posterior mean	Posterior s.d.
	ϕ_1	$(y_{t-1} - y_{t-1}*)$	0.6	0.15	0.635	0.147
IS curve	ϕ_2	$(y_{t-2} - y_{t-2}*)$	0.3	0.15	0.437	0.177
	γ_1	$(r_{t-1} - r_{t-1}*)$	0.3	0.15	0.331	0.139
Phillips curve	b_1	$(y_t - y_t*)$	0.13	0.05	0.129	0.777
	b_2	$(y_{t-1} - y_{t-1}*)$	0.11	0.05	0.134	0.139
	β_9	i_{t-1}	0.8	0.19	0.976	0.011
Taylor rule	β_{10}	$(\pi^{yoy}{}_t - \mu_t)$	1.5	0.1	1.485	0.109
	β_{11}	x_t	0.3	0.07	0.295	0.072
Natural rate	ρ_r	$r_{t-1}*$	0.95	0.025	0.948	0.035
Share of rural population	α_D		9	2	7.922	0.6112

Source: Estimated by authors

The confidence interval around the NIR estimation has been reducing (Figure 3) and averaged 1.302. The figure shows NIR trending downwards from about 2.5 in the early 2000s and is more precisely estimated in the inflation targeting period from 2014.

Even so, our focus in this paper is not the precise NIR estimate, but to show how it varies when EM features are added to the baseline model.

Figure 3: Output series for the LW model

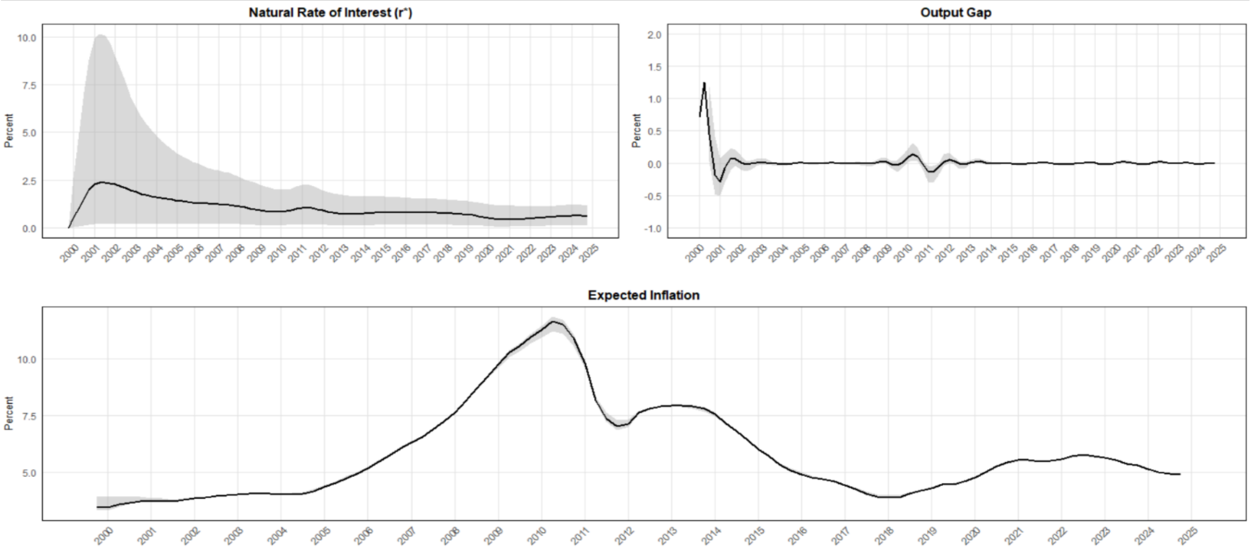


Source: Estimated by authors

5.2 LW dual

Compared to the standard (LW) framework, the inclusion of a proxy for dualism shows that structural features of India's economy meaningfully affect the NIR. Here, the posterior mean of $\alpha_D(D_t)$ at 7.92 slightly dampens the natural rate, on average by 0.184, while the other parameters remain broadly aligned with LW estimates (Table 3). The average r* over the estimation period for LW is 1.193 while for LW dual it is 1.009. The 2024 average is 0.63 compared to 0.83 for the LW. Again the precise numbers are less important than the observation that introducing structural features lowers the NIR.

Figure 4: Output series for the LW (dual) model



Source: Estimated by authors

As robustness checks, we alternatively measure the demographic proxy using agricultural employment share (41.62 per cent; World Bank), informal employment share (88.1 per cent; ILO), and rural workforce share (62.8 per cent; PLFS). These indicators capture the process of structural transformation and labour reallocation associated with economic development. Across all three specifications, the estimated coefficient remains highly stable at approximately 7.922, with a posterior standard deviation of around 0.61 in each case, confirming a robust demographic effect on the natural rate of interest (NIR). The estimated NIR series remains virtually unchanged across specifications.

The three LW dual variants based on agricultural employment share, informal employment share, and rural workforce share yield nearly identical results and show only a slight decline relative to the baseline specification using the share of rural population. The primary differences across specifications arise in the estimated output gap and potential output during the initial years of the sample period. Relative to the baseline specification, the average change in the output gap across the three alternative specifications is 0.0175, while the corresponding average change in potential output is 0.0088.

5.3 LW (realized)

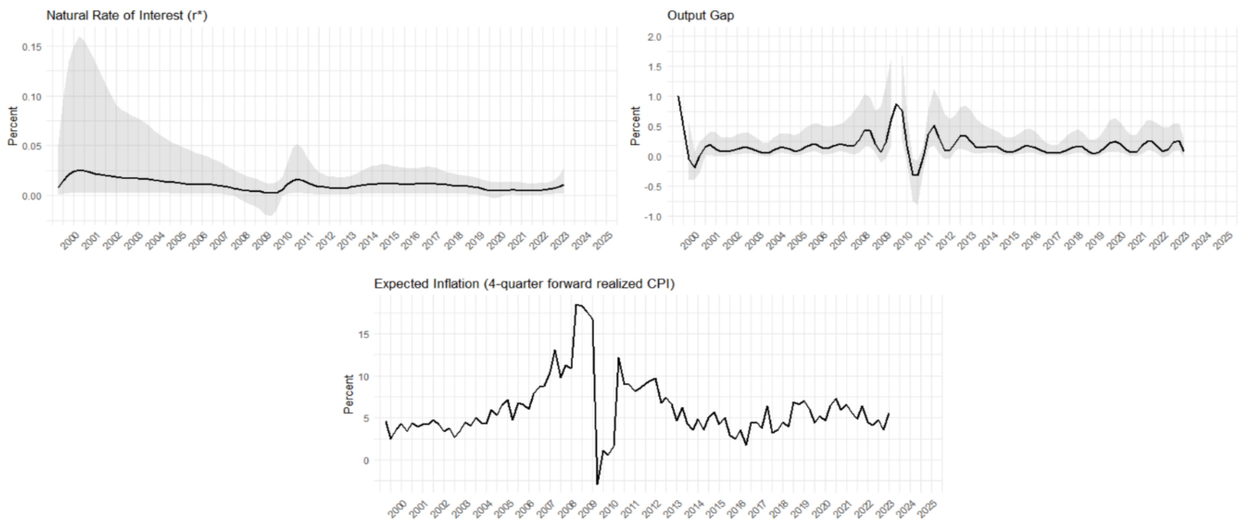
Replacing trend inflation as the estimate of expected inflation with a forward looking one period ahead measure, results in more volatile output series (Figure 5), since inflation averaging is no longer there. The estimated coefficients are not very different (Table 4). But being more forward looking also reduces average NIR to 1.12 for the estimation period, compared to 1.19 for the baseline LW model.

Table 4: Parameter estimates for the LW (realized) model

Equations	Parameters	Variables	LW framework			
			Prior mean	**Prior s.d.**	**Posterior mean**	**Posterior s.d.**
	ϕ_1	$(y_{t-1} - y_{t-1}^*)$	0.6	0.15	0.613	0.151
IS curve	ϕ_2	$(y_{t-2} - y_{t-2}^*)$	0.3	0.15	0.624	0.177
	γ_1	$(r_{t-1} - r_{t-1}^*)$	0.3	0.15	0.332	0.147
Phillips curve	b_1	$(y_t - y_t^*)$	0.13	0.05	0.152	0.085
	b_2	$(y_{t-1} - y_{t-1}^*)$	0.11	0.05	0.130	0.084
	β_9	i_{t-1}	0.8	0.19	0.973	0.011
Taylor rule	β_{10}	$(\pi^{yoy}{}_t - \mu_t)$	1.5	0.1	1.496	0.102
	β_{11}	x_t	0.3	0.07	0.295	0.072
Natural rate	ρ_r	r_{t-1}^*	0.95	0.025	0.952	0.034

Source: Estimated by authors

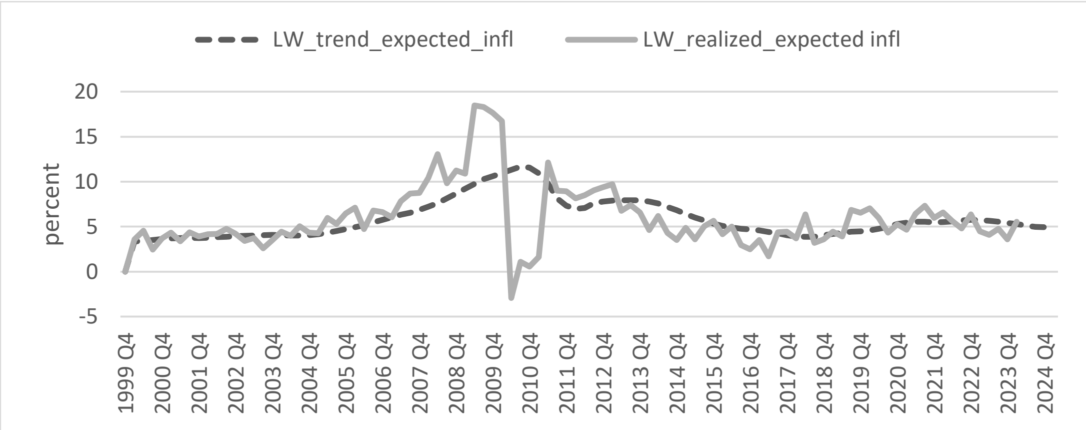
Figure 5: NIR, output gap and expected inflation series for the LW (realized)



Source: Estimated by authors

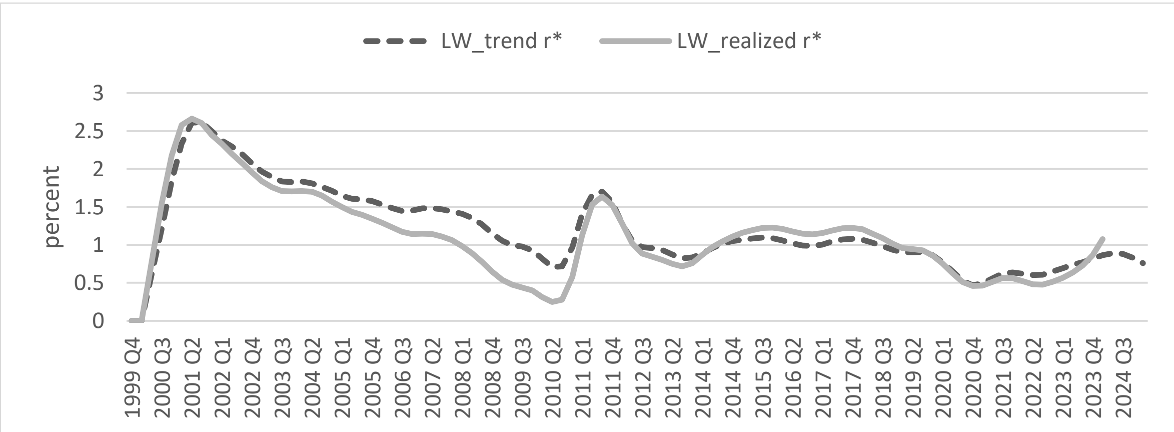
Figure 6 shows that trend inflation lags realized inflation implying NIR responds faster and more to turning points in inflation in the LW (realized) model (Figure 7).

Figure 6: Trend versus realized inflation expectations



Source: Estimated by authors

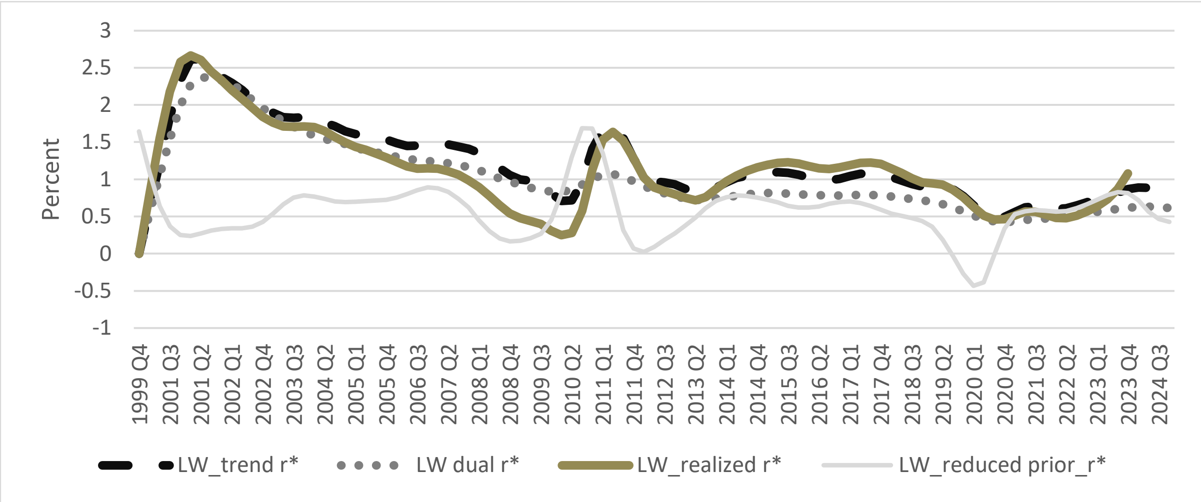
Figure 7: NIR in the LW based on trend inflation expectations versus LW (realized) NIR



Source: Estimated by authors

Figure 8 graphs the paths for NIR from the different LW models. The NIR for LW dual shows less variation than the other two, rising less but also falling less in response to shocks. LW (realized) NIR is the most volatile.

Figure 8: Comparing NIR for LW variants



Source: Estimated by authors

5.4 BN decomposition

The BN decomposition gives an even lower estimate of NIR. The average value over our estimation is 0.4.

Table 5: Parameter estimates for the BN decomposition with and without priors

Equations	**Parameters**	**Estimation**	**Significance**	**Prior mean**	**Prior s.d.**	**Posterior mean**	**Posterior s.d.**
IS curve	ϕ_1	0.629	***	0.6	0.15	0.79	0.03
	ϕ_2	0.365	***	0.3	0.15	0.14	0.03
	γ_1	0.00047	*	0.3	0.15	0.0045	0.001
Phillips curve	b_1	0.447	***	0.13	0.05	0.83	0.03
	b_2	0.313	***	0.11	0.05	0.10	0.05
Taylor rule	β_9	0.063		0.8	0.19	0.976	0.01
	β_{10}	0.3746		1.5	0.1	1.31	0.08
	β_{11}	-0.0035		0.3	0.07	0.21	0.14
Natural rate	ρ_r	-0.204	***	0.95	0.025	0.94	0.01

Source: Estimated by authors
Notes: *** $p < 0.1\%$, ** $p < 1\%$, * $p < 5\%$.

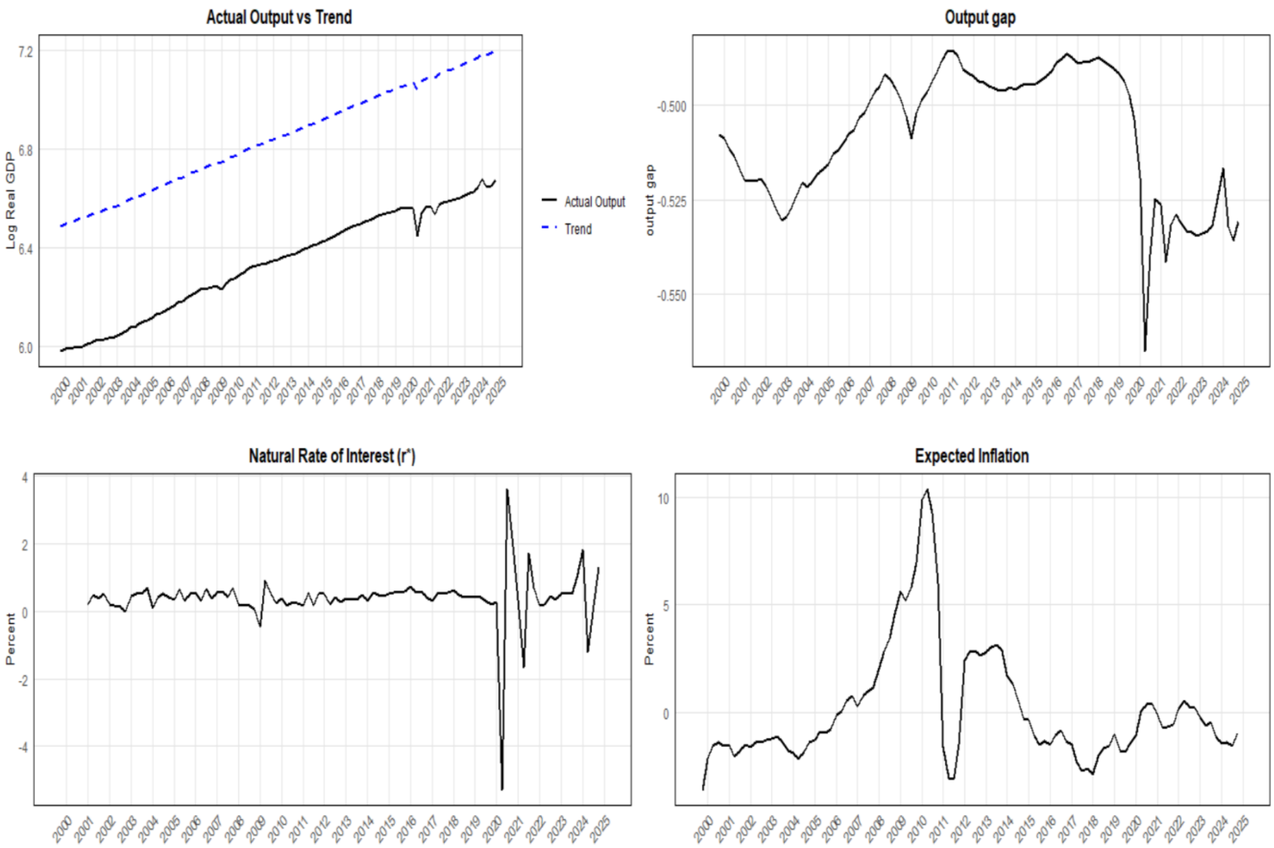
It returns a higher trend or permanent component, so that the output gap is always negative. The negative estimated ρ_r without a prior mean imposed (the LW models have a prior of 0.95) implies a large variation in the NIR with permanent output. No priors are imposed in the BN estimation in order to see what the data tells us. NIR falls and then fluctuates steeply, especially in the pandemic period when permanent output fell. In 2024 it averaged 0.38, despite fluctuations.

The correlation between permanent (trend) and temporary (output gap) shocks is estimated to be 0.119.

The combined impact of the contemporaneous and lagged output gaps is higher and the effect of the interest rate gap is small but marginally significant. Inflation gap responds strongly to both current and past output gaps in the estimated Phillips curve relationship, falling as output gaps become more negative in the post-pandemic period (Table 5).

Taylor rule variables show weak direct significance, suggesting that inadequate central bank reactions to inflation and output may have kept the output gap negative in the period.

Figure 9: BN decomposition

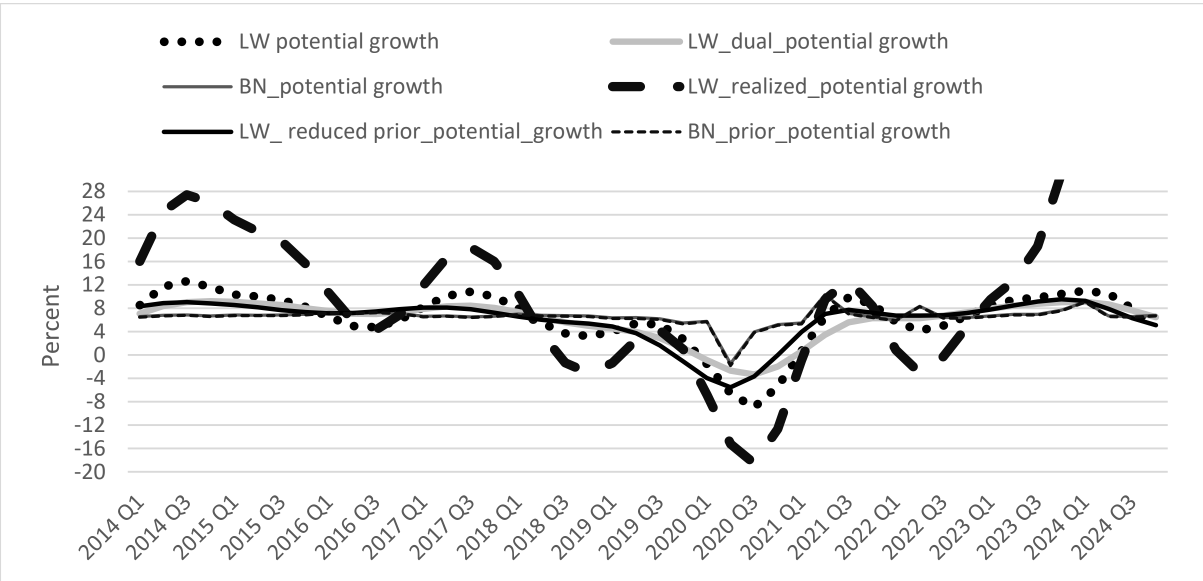


Source: Estimated by authors

5.5 Changing priors

In view of the negative output gap in the BN model, we try simulations with priors changed, to see the extent to which Bayesian priors maybe affecting results. Priors are reduced in the LW model and introduced in the BN model. Priors do affect coefficients, but the primary impact seems to be from the statistical structure imposed on the unobserved variables. Priors used are consistent with a range of estimates for the NK model with a flat PC and high interest elasticity of the IS and are required because of the large number of coefficients to be estimated and the 3 unobservable variables to be extracted. While data-consistency is also necessary, in a simultaneous equation structure, identification can be inadequate without behavioural restrictions.

Figure 10: Comparing potential growth from all the models



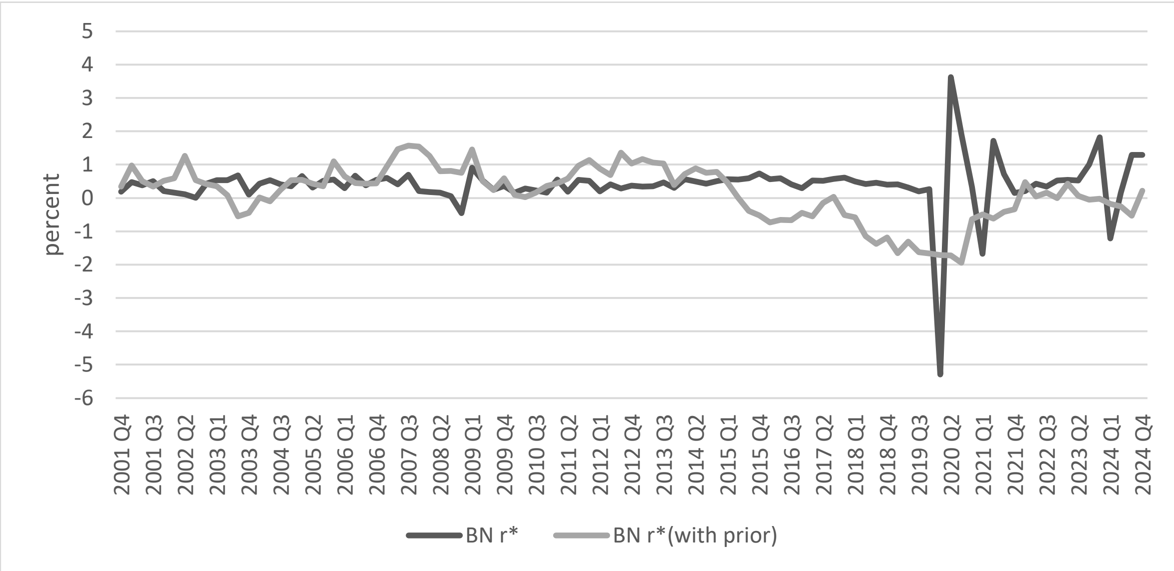
Estimates for the case when priors are reduced to half for the aggregate demand parameters as well as for the lagged r* in the LW model, are reported in Table 3a and graphed in figures 8 and 10. Estimated average NIR is lower at 0.57 compared to 1.19 for the baseline LW model. In Q4 FY24 it is 0.43 compared to 0.76. Changing the prior on lagged r* makes r* more volatile. NIR changes more and faster than even the realized LW r*, but as a result the potential growth (Figure 10) is less volatile. All CBs smooth medium-run policy rates, but some reduction in smoothing may be required to reduce output volatility.

The BN estimation with priors for the NK part improves the coefficient estimates. With a smoothing prior on lagged r*, spikes are removed yet the NIR is more responsive (Figure 11); average r* falls further to 0.147. Interest elasticity of demand increases, but still remains low.

The potential growth and the output gap, however, change only marginally. The output gap is still large and negative.

Estimated potential growth paths (y-o-y) from 4 of the models are close and reach 10% in the 2010s and 2020s with a sharp dip in the pandemic period. The realized inflation LW creates much more volatility in potential growth, which is very high preceding a period of low inflation such as in 2014 and in 2024 (Figure 10). Policy did not allow actual output to rise to match the space available in these periods. The LW baseline model also has higher volatility.

Figure 11: Comparing BN NIRs



Source: Estimated by authors

6. Conclusion

A model used for actual policy has to impose all kinds of lags and smoothing as well as remove outliers in the data to be able to extract unobserved policy decision variables. And these extractions have large error bands.

The purpose of our estimations, however, is not to arrive at a model for policy decisions. Our aim is to produce a reasonable replica of the policy model used in order to introduce emerging market features and understand their impact.

The estimated baseline model and the variants all support the growing maturity of the Indian macroeconomy so that flexible inflation targeting is feasible. Error bands are lower in the inflation targeting period as is the volatility of inflation, despite large external shocks. The estimated NIR falls to about unity in the baseline model in the inflation targeting period from about 2 in the 2000s. Estimated IS and Phillips curves are well behaved.

All the estimated variants tend to lower the NIR further. Priors and statistical assumptions help estimation, but in a way impose our preconceptions on the data. The purely data based BN decomposition, which allows correlation between the cycle to affect the trend, as is the case under non steady-state growth, suggests that output has always been below potential and the latter is only affected by major shocks such as the pandemic. The NIR is substantially lowered.

Policy needs to smooth shocks and take additional steps to raise actual output. While inflation volatility has fallen, growth volatility also needs to be reduced. This requires keeping real rates lower. The view that higher growth raises the EME NIR is not supported.

References

Aguiar, M., Gopinath, G. 2007. 'Emerging market business cycles: the cycle is the trend.' *Journal of Political* Economy, 115(1): 69–102. https://www.jstor.org/stable/10.1086/511283

Basistha, A. and Nelson, C. R. 2007. 'New measures of the output gap based on the forward-looking new Keynesian Phillips curve.' *Journal of Monetary* Economics, 54(2): 489–511. https://www.sciencedirect.com/science/article/pii/S0304393206001139

Behera, H.K. 2024. 'Updating estimates of the natural rate of interest for India with post-pandemic evidence.' *RBI Bulletin*, July, pp. 77-89. https://www.rbi.org.in/Scripts/BS_ViewBulletin.aspx?Id=22718

Blanchard, O. J. and Quah, D. 1989. 'The Dynamic Effects of Aggregate Demand and Supply Disturbances' *The American Economic Review*, 79(4): 655–673. https://www.jstor.org/stable/1827924?seq=1

Borio, C., Disyatat, P. and Rungcharoenkitkul, P. 2019. 'What anchors for the natural rate of interest?' BIS Working Papers, No 777. https://www.bis.org/publ/work777.pdf

Cover, J. P., Walter, E. and C. J. Hueng. 2006. 'Using the Aggregate Demand-Aggregate Supply Model to Identify Structural Demand-Side and Supply-Side Shocks: Results Using a Bivariate VAR' *Journal of Money, Credit and Banking*, 38(3): 777–790. https://www.jstor.org/stable/3839091?seq=1

Goyal, A. 2009. 'The natural interest rate in emerging markets.' Chapter in 'New and Enduring Themes in Development Economics.' Edited by Dutta, B., Roy, T. and Somanathan, E, pp. 333-368. World Scientific Publishers. https://doi.org/10.1142/9789812839428_0015

Goyal, A. and S. Arora. 2016. 'Estimating the Indian natural interest rate: a semi-structural approach.' *Economic Modelling*, 58: 141–153. November. https://doi.org/10.1016/j.econmod.2016.05.023

Goyal, A. and Goel, G. 2019. 'Correlated Shocks, Hysteresis, and the Sacrifice Ratio: Evidence from India' *Emerging Markets Finance and Trade*, 57(10): 2929-2945. https://www.tandfonline.com/doi/full/10.1080/1540496X.2019.1668770

Goyal A. and Kumar A. 2018. 'Active Monetary Policy and the Slowdown: Evidence from DSGE-based Indian aggregate demand and supply' *The Journal of Economic Asymmetries*, 17(June): 21-40. https://doi.org/10.1016/j.jeca.2018.01.001

Goyal, A. and Ray, S. 2025. 'Reducing supply shock-led inflation in emerging markets.' *Economic Analysis and Policy*, 86(June): 2278-2301. https://doi.org/10.1016/j.eap.2025.05.024

IMF. 2015. 'Regional economic outlook: Asia and Pacific Stabilizing and outperforming other regions.' *International Monetary Fund*, April. https://www.imf.org/en/publications/reo/apac/issues/2017/01/07/regional-economic-outlook-asia-and-pacific5

IMF. 2023. 'The natural rate of interest: drivers and implications for policy.' Chapter 2 in World Economic Outlook, *International Monetary Fund*, April, pp. 45-67. https://www.imf.org/-/media/files/publications/weo/2023/april/english/ch2.pdf Blog https://www.imf.org/en/Blogs/Articles/2023/04/10/interest-rates-likely-to-return-towards-pre-pandemic-levels-when-inflation-is-tamed

Laubach, T. and J. C. Williams. 2003. 'Measuring the Natural Rate of Interest.' *The Review of Economics and Statistics*, 85(4): 1063–1070. https://www.jstor.org/stable/3211826?seq=1

Pattanaik, S., H.K. Behera and S. Sharma. 2022. 'Revisiting India's natural rate of interest.' *RBI Bulletin*, June, pp. 89-99. https://www.rbi.org.in/Scripts/BS_ViewBulletin.aspx?Id=21068

Platzer, J. and Peruffo, M. 2022. 'Secular drivers of the natural rate of interest in the United States: a quantitative evaluation.' IMF Working Paper No. 2022/030. https://www.imf.org/en/publications/wp/issues/2022/02/11/secular-drivers-of-the-natural-rate-of-interest-in-the-united-states-a-quantitative-512755