CENTRE FOR CENTRAL BANKING STUDIES

ECONOMIC MODELLING AND FORECASTING

Estimating a monetary policy model (without money) for India

by

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[1] Sections denoted by an asterisk (*) can be skipped without loss of continuity.

1   Introduction

The aim of this exercise is to estimate a new Keynesian (NK) model for India. As such, we are trying to replicate IMF Working Paper WP/10/183 by Patra and Kapur (2010). Using an augmented version of the canonical three-equation NK model, the authors find that their estimated model yields valuable insights into the functioning of the Indian economy, most notably the monetary transmission mechanism. This is of great importance in light of the fact that, as outlined in the paper, the monetary policy framework in India has undergone fundamental modifications. The authors summarise their findings as follows:

- aggregate demand reacts to interest rate changes with a lag of at least three quarters, with inflation taking seven quarters to respond;
- inflation shows a lot of inertia and persistence when it sets in, irrespective of its source;
- exchange-rate pass-through to domestic inflation is low;
- inflation turns out to be the dominant focus of monetary policy, accompanied by a strong commitment to the stabilisation of output; and
- recent policy actions by the Reserve Bank of India (RBI) have raised the effective policy rate, but the estimated natural policy rate suggests some further tightening to normalise the policy stance.

One aim of this exercise is therefore to take a theoretical model to (emerging-market) data and illustrate how we can enrich such models with country-specific considerations. The other is to illustrate how the individual equations of an NK model can be estimated using the generalised method of moments (GMM).

2   The new Keynesian paradigm

The new Keynesian paradigm arose in the 1980's as an attempt to provide microfoundations for key Keynesian concepts such as the inefficiency of aggregate fluctuations, nominal price stickiness and the non-neutrality of money.[2] In the process, behavioural equations describing aggregate variables were replaced by first-order conditions derived from explicit intertemporal optimisation problems facing agents in the economy. One of the aims of this new approach was to make models robust to the Lucas critique (1976), such that they could be used for policy analysis.

Today, the new Keynesian framework has emerged as the workhorse for the analysis of monetary policy and its implications for inflation, macroeconomic fluctuations and welfare. It constitutes the backbone of the new generation of (medium-scale) models already in use or under development in many central banks and international financial institutions around the world. In addition, it has provided the theoretical underpinning for the inflation stability-oriented strategies adopted by the majority of central banks in the industrialised world (…and increasingly in emerging-market and developing economies as well).

All in all, the **new neoclassical synthesis** or the **new Keynesian model** has become an influential and powerful tool in macroeconomic research. In brief, inflation and output respond to aggregate demand, aggregate demand responds to interest rates and interest rates are set, in turn, in response to expected movements in output and inflation. A salient feature of new Keynesian models is the absence of money, which plays no explicit role in these models (even abstracting from the existence of a monetary sector). This does not imply that money does not matter: money is still central, but it is unseen.

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[2] The new Keynesian revolution in economics is described in, *inter alia*, Woodford (1999) and Dixon (2008).

The key elements and properties of new Keynesian models are as follows:

- **monopolistic competition**: The prices of goods and inputs are set by private economic agents in order to maximise their objectives, rather than by an anonymous Walrasian auctioneer seeking to clear all (competitive) markets at once. Firms therefore use their market power to maintain their prices above marginal cost, so that even if they fail to set prices optimally, they will remain profitable.

- **nominal rigidities**: Firms are subject to some constraints on the frequency with which they can adjust the prices of the goods and services they sell (a process known as 'Calvo' pricing, following Calvo (1983)). Alternatively, firms may face some costs of adjusting those prices (a process known as 'Rotemberg' pricing, following Rotemberg (1982)). The same kind of friction applies to workers in the presence of sticky wages.

- **short-run non-neutrality of monetary policy**: As a consequence of the presence of nominal rigidities, changes in short-term nominal interest rates (whether chosen directly by the central bank or induced by changes in the money supply) are not matched by one-to-one changes in expected inflation, thus leading to variations in real interest rates. These, in turn, bring about changes in consumption and investment and, as a result, in output and employment, because firms find it optimal to adjust the quantity of goods supplied to the new level of demand. In the long run, however, all prices and wages adjust, meaning the economy reverts back to its natural equilibrium.

The new Keynesian model thus underscores the importance of the natural levels of output and the interest rate, which are the values for these variables that would arise in equilibrium without nominal rigidities.

3 The canonical three-equation new Keynesian model

The intuitive appeal of the canonical NK model is its simplicity in characterising the structure of the economy and (monetary) policy design: it reduces the economy to a three-equation system comprising an aggregate supply or new Keynesian Phillips curve, an aggregate demand or (dynamic) IS curve and a monetary policy reaction function. As a general equilibrium model, it has two advantages: one, the Phillips curve and the IS curve are based on microeconomic foundations and factor in forward-looking (rational) behaviour on the part of economic agents; and two, the monetary policy reaction function depicts more accurately the operating procedure of modern central banks than do competing models.

3.1 Aggregate supply: the new Keynesian Phillips curve

Using a Calvo-type price adjustment, Woodford (2003) illustrates how the aggregation of the linearised optimal price adjustment rules for individual firms yields an expression in current inflation, π_t, expected future inflation, $E_t(\pi_{t+1})$, and a measure of aggregate marginal cost, mc_t:

$$\pi_t = \gamma_f\, E_t(\pi_{t+1}) + \lambda\, mc_t + u_t \tag{1}$$

This is the **new Keynesian Phillips curve** (NKPC), where the coefficients γ_f and λ are themselves functions of **deep** or **structural** parameters, which are by definition assumed to be invariant to regime changes. For example, the **deep** or **structural** coefficient on expected inflation, γ_f, is the household's subjective discount factor. Overall, the optimisation-based approach places a tight structure on the relations. The random disturbance, u_t, is often interpreted as an exogenous shock to firms' mark-up or, in

the parlance of Clarida *et al.* (1999), a 'cost-push shock'. Solving equation (1) forward, one can see that current and expected future marginal costs are driving today's inflation.

This forward-looking process for inflation contrasts sharply with the traditional Phillips curve, which typically relates inflation to lagged values of itself as well as some measure of excess demand, conventionally the unemployment rate, without any explicit theoretical motivation. At the same time, though, equation (1) has the flavour of a traditional Phillips curve in the sense that it relates current inflation, π_t, to excess demand as measured by mc_t, and a term that reflects inflation expectations, in this case $\gamma_f E_t(\pi_{t+1})$.

Another important way in which the NKPC differs from the traditional Phillips curve is that it is fully forward-looking. Inflation depends not only on the current values of mc_t and u_t, but also on the expected discounted sequence of their respective future values. Note that this forward-looking property of inflation implies that a central bank's success in containing inflation depends not only on its current policy stance, but also on what the private sector perceives the stance to be in the future.

The empirical performance of the NKPC in equation (1) has come under some criticism. In the critical camp, Fuhrer and Moore (1995) gave an early negative assessment of its empirical performance. Along the same lines, Rudebusch and Svensson (1999) stressed that a purely backward-looking Phillips curve had a lot more support from the data. In a similar vein, Mankiw and Reis (2002) conducted a quantitative review of the perceived shortcomings of the NKPC and described an alternative price-setting mechanism based on the assumption of sticky information. On the other hand, Galí and Gertler (1999), Galí *et al.* (2001) and Sbordone (2002) provided more favourable evidence of the empirical fit of equations relating inflation to marginal cost and also discussed the difficulties in estimating or testing the NKPC given the fact that the output gap is a latent, or unobservable, variable.

For most measures of inflation and what could be considered reasonable measures of marginal cost, inflation tends to be more persistent than marginal cost. Since marginal cost 'drives' inflation in the basic NKPC in equation (1), this makes it hard for the model to match the data. Economists have therefore modified the basic NKPC by introducing 'rule-of-thumb' price adjusters or firms that simply index their price to the aggregate inflation rate, e.g., Galí and Gertler (1999). This is accomplished by modifying the Calvo framework in such a way as to assume that amongst the firms able to adjust prices in a given period, only a fraction set prices optimally, i.e., on the basis of expected future marginal costs. The remaining fraction of firms uses a simple rule-of-thumb, whereby prices are set equal to the average of newly adjusted prices in the last period plus an adjustment for expected inflation, based on lagged inflation. In other words, the fraction of firms that cannot choose their price freely can in fact adjust it in part to catch up with recent inflation. These assumptions lead to the inclusion of lagged inflation:

$$\pi_t = \gamma_b \, \pi_{t-1} + \gamma_f E_t(\pi_{t+1}) + \lambda \, mc_t + u_t \tag{2}$$

which makes this modified NKPC a hybrid of the basic NKPC (with a forward-looking inflation component) and more standard Phillips curve (with a backward-looking inflation component) and improves the model's ability to fit the observed inflation data.[3] The coefficients γ_b, γ_f and λ are again functions of structural parameters. The ability of monetary policy to control inflation with the NKPC depends on the relative magnitudes of these coefficients. A discussion of this can be found in, *inter alia*, Galí (2008b). Loosely speaking, monetary policy affects inflation through its effects on marginal cost. Thus, the smaller the coefficient on marginal cost, the less impact monetary policy will have on inflation. In the extreme, when $\lambda = 0$, inflation evolves independently of monetary policy and, in fact, from whatever else happens in the economy. In turn, the coefficients on past and future inflation, γ_b and γ_f respectively, determine how 'costly' it is to reduce inflation. If the coefficient on lagged inflation, γ_b, is

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[3] Note that, as discussed in Galí *et al.* (2005), the hybrid NKPC nests the pure forward-looking NKPC based on the Calvo model as a special case if $\gamma_b = 0$.

large, then inflation is mostly driven by its own past and policy actions might affect inflation only with a (long) time lag.

In empirical analyses, however, specifications of the hybrid NKPC are augmented to include other variables. In Galí and Gertler (1999) and Galí *et al.* (2005), the authors estimate a hybrid version of the NKPC where inflation depends on both lagged and expected future inflation.[4] These two papers also include unit labour costs, while Mehra (2004) considers supply shocks. In addition, Goodhart and Hofmann (2005b) included primary commodity prices. The inclusion of additional explanatory variables may be at odds with the theoretical underpinnings of the model, but such an extended model has been found to have better explanatory power and deliver the right signs on estimated coefficients.

Patra and Kapur also argue that global commodity prices and exchange-rate movements, which are prone to significant short-term volatility, are important determinants of (short-term) inflation in India. Empirical evidence for the former is provided by, *inter alia*, Batini *et al.* (2005). Furthermore, both Ho and McCauley (2003) and Ito and Sato (2008) have stressed the significance of the exchange rate in the evolution of domestic inflation, above all for emerging market economies. For those reasons, the hybrid NKPC for India is augmented by global commodity price inflation, π_t^*, and the (year-on-year) change in the nominal exchange rate of the Indian rupee against the US dollar, Δey_t.

$$\pi_t = a_0 + a_1\, mc_t + a_2\, E_t(\pi_{t+1}) + a_3\, \pi_{t-1} + a_4\, \pi_t^* + a_5\, \Delta ey_t + u_t \tag{3}$$

where the expected signs on the coefficients are as follows: $a_1, a_2, a_3, a_4, a_5 > 0$.

More information about the NKPC can be found in the Fall issue of the Federal Reserve Bank of Richmond's *Economic Quarterly* (2008), which is dedicated solely to the NKPC. The five papers provide an introduction to the NKPC, describe its history and development, lessons from single-equation econometric estimation, an illustration of DSGE-model-based estimation and some policy implications of the nominal rigidities underlying the NKPC.[5]

3.2   Aggregate demand: the dynamic IS curve

The new Keynesian aggregate demand or (dynamic) IS curve is derived from the log-linearised consumption Euler equation of intertemporally optimising households under a market-clearing condition. In contrast to the traditional IS curve, current output in the dynamic IS curve – generally defined as the output gap, i.e., the deviation of current from potential output – depends on expected future output and the real interest rate. As individuals prefer to smooth consumption in response to higher future incomes, expectations of higher future output induce them to consume more in the current period. As in the standard theory, current output is inversely related to the real interest rate, with the interest elasticity of output representing the intertemporal elasticity of substitution between consumption and saving:

$$y_t = b_1 E_t(y_{t+1}) + b_2(i_t - E_t(\pi_{t+1})) + v_t \tag{4}$$

where y_t is the output gap, π_t is the inflation rate (or the deviation of the inflation rate from an implicit or explicit inflation target), i_t is the nominal interest rate and v_t reflects demand shocks.

Iterating equation (4) forward, we find that the current output gap depends not only on the current real interest rate but also on its expected future path. This means that to the extent that monetary policy has control over the real interest rate on account of nominal rigidities, expected as well as current policy actions affect aggregate demand (Clarida *et al.* (1999)).

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[4] Lagged inflation enters the hybrid NKPC because a fraction of firms set prices using a backward-looking rule-of-thumb.
[5] Another very informative paper on the topic of identifying the NKPC is Nason and Smith (2008b).

Once again we find that backward-looking as well as hybrid specifications of the IS curve have been found to match the (lagged) response of output to monetary policy better in empirical applications than the theoretical and purely forward-looking version. Empirical evidence for this claim can be found in, for example, Peersman and Smets (1999), Rudebusch and Svensson (1999) and Rudebusch (2002).

But we note that backward-looking expectations in the IS curve may be inconsistent with theory, which is why recent theoretical advances incorporate situations in which household utility depends on lagged consumption. This is achieved by assuming habit persistence in the consumption behaviour of households (Fuhrer (2000)). The consumption habit is a source of richer, and more realistic, output dynamics in response to changes in the interest rate. Taking into account these considerations, the IS curve can be formulated as:

$$y_t = b_0 + b_1 E_t(y_{t+1}) + b_2(i_t - E_t(\pi_{t+1})) + b_3 y_{t-1} + v_t \tag{5}$$

When put to the empirical test, though, the evidence relating to the hybrid IS curve is mixed. Nelson (2002) as well as Goodhart and Hofmann (2005a,b) are examples of studies in which an estimated backward-looking IS curve for industrialised countries fails to yield a significant negative relationship between the real interest rate and the output gap ($b_2 < 0$). One argument put forward for the failure to find such a significant relationship is an omitted variable problem, as other key determinants of aggregate demand are left out of the equation.[6] In fact, papers that have incorporated additional variables obtained the required significantly negative coefficients on the real interest rate (b_2).

Patra and Kapur (2010) therefore argue for an extended version of the hybrid Indian IS curve in equation (5). In particular, the equation is augmented with variables that are meant to represent significant demand-side effects in the evolving Indian context: `yagr` (real agricultural output, expressed in terms of deviations from trend), `x` (real world exports, expressed in terms of deviations from trend), `reer` (the real effective exchange rate, expressed in terms of deviations from trend), `nfc` (the year-on-year rate of change in non-food bank credit) and `bses` (the year-on-year rate of change in the Bombay Stock Exchange's SENSEX index):

$$y_t = b_0 + b_1 E_t(y_{t+1}) + b_2(i_t - E_t(\pi_{t+1})) + b_3 y_{t-1} + b_4 yagr_t + b_5 x_t + b_6 reer_t + b_7 nfc_t + b_8 bses_t + v_t \tag{6}$$

where the expected signs on the coefficients are as follows: $b_1, b_3, b_4, b_5, b_7, b_8 > 0$ and $b_2, b_6 < 0$.

3.3 Monetary policy reaction function: the Taylor rule

The model is closed using a monetary policy reaction function. As has become customary, the monetary authority adjusts the nominal interest rate to minimise volatility in output and inflation. This results in a specification equivalent to a Taylor rule. The theoretical literature on the specification of Taylor rules recommends a forward-looking specification. In this case, the interest rate is adjusted in response to future inflation and output deviations from an inflation target and potential output respectively, meaning that the target variables depend not only on the current policy stance, but also on expectations of future policy. In contrast, the empirical literature on Taylor rules (Clarida *et al.* (2000) and Páez-Farrell (2009), for example) finds that a specification with both backward- and forward-looking terms provides the best fit to the data, especially when a lagged interest-rate term is included to capture inertia in the policy response of central banks (also known as interest-rate smoothing). The general specification of the monetary policy reaction function therefore takes the form:

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[6] Goodhart and Hofmann (2005a), for example, argue that interest rate effects on output are indirectly transmitted through these variables.

$$i_t = c_0 + c_1 E_{t-j}(\pi_{t+k}) + c_2 E_{t-j}(y_{t+m}) + c_3 i_{t-1} + w_t \tag{7}$$

where i_t is a (short-term) nominal interest rate (the monetary policy variable), π_t is the deviation of inflation from its (either implicit or explicit) target value, c_0 is the equilibrium or natural rate of interest, and y_t denotes the output gap. In equation (7), j represents the possible information lag with which the central bank operates. Finally, if $k = m = 0$, equation (7) reduces to the original Taylor rule under which the central bank responds to **current** values of inflation and the output gap. Alternative versions of the Taylor rule are obtained by changing the values for k and m: if k and m are both positive, we get a forward-looking version of the Taylor rule, while the outcome is backward-looking if k and m are negative. In their analysis of the optimal choice of lead structure, Taylor and Williams (2010) fail to find significant benefits from including expectations more than one year out for US inflation or beyond the current quarter for the US output gap.

In addition, as in the case of the NKPC and the IS curve, open-economy considerations mean that the Taylor rule (7) may need to be augmented by additional variables. In fact, since its original formulation, the Taylor rule has been extended to include additional − external − variables, above all a real exchange rate term, q_t, in either levels or changes (Ball (1999), Batini *et al.* (2003), Taylor (2001)):

$$i_t = i_t^* + \rho_i i_{t-1} + (1 - \rho_i)(\lambda_1(\pi_t - \pi_t^*) + \lambda_2(y_t - y_t^*) + \lambda_3(q_t - \lambda_4 q_{t-1})) \tag{8}$$

where q_t is the deviation of the real exchange rate in period t from its natural (or steady-state) equilibrium value.[7] Taylor (2001) speculated that estimated Taylor rules such as (8) were unlikely to yield a strong independent exchange rate effect, as the effect of the exchange rate on output and inflation was already explicitly accounted for by the central bank. We should note that including the exchange rate in the monetary policy reaction function does **not** necessarily imply setting an exchange rate target. Doing so would imply a potential conflict for monetary policy: if monetary policy responds to deviations of the level of the exchange rate from an estimated steady-state value, any errors in estimating the long-term equilibrium level may lead to systematic biases in the stance of monetary policy - and thus a conflict between the inflation and exchange rate objectives.

Adding to the empirical evidence, Aizenman *et al.* (2011) investigated Taylor rules of the form:

$$i_t = i_t^* + \rho i_{t-1} + (1 - \rho)(\lambda_1(\pi_t - \pi_t^*) + \lambda_2(y_t - y_t^*) + \gamma X_t) \tag{9}$$

where X_t can be an external variable such as the change in the real exchange rate, the current account or reserve accumulation. The authors found that the real exchange rate change, as well as changes in international reserves, are highly significant in a panel of 16 emerging market economies. The response to the real exchange rate is explained by regarding the current real exchange rate as an indicator of future inflation.

Patra and Kapur therefore include the US federal funds rate (i_t^*) and the annualised quarter-on-quarter variation in the nominal exchange rate of the Indian rupee against the US dollar (Δeq_t). The estimated monetary policy reaction function for India therefore takes the form:

$$i_t = c_0 + c_1 E_{t-j}(\pi_{t+k}) + c_2 E_{t-j}(y_{t+m}) + c_3 i_{t-1} + c_4 \Delta eq_t + c_5 i_t^* + w_t \tag{10}$$

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[7] We note that equation (8) allows for dampening volatility in the **level** of the exchange rate relative to the long-run value, **changes** in the exchange rate or both. If $\lambda_4 = 0$, the central bank systematically dampens deviations in the **level** of the real exchange rate from the steady-state equilibrium value. On the other hand, if $\lambda_4 = 1$, the central bank dampens **changes** in the real exchange rate, consistent with limiting exchange rate volatility. Finally; if $0 < \lambda_4 < 1$, the central bank places some weight on dampening rapid changes in the exchange rate as well as limiting exchange rate misalignment.

with the values of k and m to be decided empirically. The expected signs on the coefficients are as follows: c_1, c_2, c_3, c_4, $c_5 > 0$.

Exchange-rate changes are included as exchange-rate smoothing has been found to be an important policy consideration in the policy reaction function of most emerging market economies, as documented in Mohanty and Klau (2004). In particular, the authors estimated modified Taylor rules for 13 emerging market and transition economies, complementing inflation, the output gap and lagged interest rates with current and lagged real exchange rate changes. On the basis of OLS estimation, they found statistically significant coefficients on real exchange rate changes in ten out of the 13 countries, with the policy response to exchange rate changes being frequently larger than the response to inflation and the output gap. This was taken to be evidence of the 'fear of floating' hypothesis, first postulated by Calvo and Reinhart (2002). This line of research was later extended by Edwards (2006), who investigated the determinants of the exchange-rate response in Taylor-rule regressions.

Moreover, in light of the increasing degree of trade and financial integration, large capital flows and potential business cycle synchronisation, key foreign interest rates can have significant effects on domestic monetary policy, which is why the US federal funds rate is included in equation (10).[8]

It is worth noting that (i) the output gap is a latent, or unobserved variable, and that (ii) GDP data is subject to frequent and often sizeable revisions. As a result, there can be large divergences between real-time data on which authorities make their policy judgements and the final revised data that are used for empirical work. Following a recommendation by Taylor and Williams (2010), Patra and Kapur therefore also explore an alternative formulation of the Taylor rule in which the output gap variable is replaced by its first difference.

4   Data

The quarterly data span the period from 1996 Q2 to 2009 Q3 and are contained in the EViews workfile **imf_india.wf1**.[9] The span of the data is determined by the availability of quarterly data on real GDP for India. More details on the underlying data series, data construction and data manipulation can be found in Section V in Patra and Kapur (2010). To open the EViews workfile from within EViews, choose **File**, **Open**, **EViews Workfile…**, select **imf_india.wf1** from its current location, update the default directory by checking the small box and click **Open**. Alternatively, you can double-click on the workfile icon outside of EViews, which will open EViews automatically.

A word of caution is in order. In preparing the exercise, I noted some occasional slight differences between the authors' estimates and my replications. This has two reasons. First, different software packages are used in the empirical estimation: Patra and Kapur run all of their estimations in RATS, while we will be using EViews for this purpose. Second, these differences are especially apparent in regressions involving inflation data. Figure 1 shows the three inflation measures that are contained in **india_imf.wf1**.

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[8] Interestingly, Kendall and Ng (2013) estimated a variety of Taylor rules for New Zealand to analyse whether the behaviour of monetary policy in New Zealand, Australia and the US has changed in the wake of the global financial crisis. While they found no evidence of a direct response to the **exchange rate**, they did find a significant response to **long-term US interest rates**: short-term interest rates in New Zealand appear to respond to global financial conditions.

[9] I would like to thank Muneesh Kapur from the Reserve Bank of India for providing me with (almost all) of the original data.

Figure 1: Alternative indicators of Indian inflation
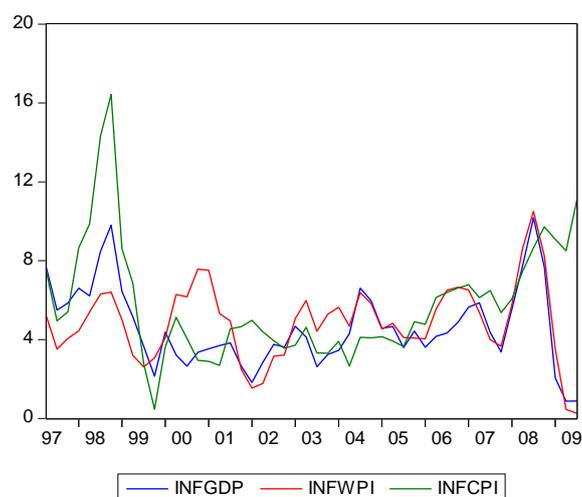
This figure is slightly different from Chart 2 on page 23 in [Patra and Kapur (2010)](#). In particular, `infwpi` in my EViews workfile seems to behave differently from the one used in the original paper. This may explain some of the discrepancies between my estimation results and those found in Patra and Kapur.

5   Estimation results

The three-equation NK model of the Indian economy described in Section 3 (and given by equations (3), (6) and (10)) is estimated on quarterly data from 1996 Q2 to 2009 Q3. The robustness of the estimation results is assessed by looking at two sub-period of the data. To begin with, the authors estimate the model over the period from 1996 Q2 to 2008 Q2 (i.e., ending before the collapse of Lehman Brothers). A second period runs from 2002 Q2 to 2008 Q2 and coincides with substantial changes in the operating framework of Indian monetary policy.[10]

As we will see, the results for these two truncated samples are very similar to the estimates for the full period, attesting to the stability of the estimated model. The results for the two sub-samples can be found in Appendix 2 (and are left as an optional exercise).

Single-equation estimation of the NK model parameters is appealing because it does not require any assumptions about how the rest of the economy should be specified. Yet standard ordinary least squares (OLS) estimation of the NK model is not applicable, since most of the three equations involve future expected values as an endogenous variable that is correlated with the error term of the estimation equation. In principle we could use two-stage least squares (TSLS) to estimate the model equations. To do so, we would require the following conditions: first, that we have good instruments (i.e., instruments that are not correlated with the equation's residuals but which are correlated with the regressors); second, if we use actual values as proxies for any expected future values, then we must augment our equation using moving average errors (theory should help us in determining the exact nature of these errors); and third, we must ensure that our residuals are well behaved (i.e., no autocorrelation or heteroskedasticity) by adding sufficient lags and possibly correcting for heteroskedasticity. It is in this last point that the generalised method of moments (GMM) appears to be superior to TSLS as GMM can correct for

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[10] Interested readers are referred to Patra and Kapur (2010, Section III) for more details on changes in the Indian monetary policy framework.

unknown forms of autocorrelation and heteroskedasticity. Therefore, as pointed out in, *inter alia*, Nason and Smith (2008), consistent parameter estimates can be obtained using GMM.[11]

5.1   The dynamic IS curve

We now estimate the new Keynesian aggregate demand or (dynamic) IS curve using GMM. The GMM estimation methodology in EViews is set up as an instrumental variables approach. The theoretical relations that the parameters should satisfy, i.e., the population moment or orthogonality conditions, between some (possibly non-linear) function of the data, X, and parameters, θ, $f(X,\theta)$ and a set of q instrumental variables, $Z = (z_{1t}, z_{2t}, \ldots , z_{qt})$ are given by:

$$E[Z_t(yt - f(X,\theta))] = E[Z_t'\varepsilon_t] = 0 \tag{11}$$

where θ is the vector containing the parameters to be estimated. The GMM estimator selects parameter estimates for the vector θ such that the sample correlations between the instruments and the function $f(\bullet)$ are as close to zero as possible, as defined by the criterion function:

$$J(\theta) = (m(y, X; \theta))'Wm(y, X; \theta) \tag{12}$$

where $m(y, X; \theta)$ collects the q individual $Z_t(y_t - f(X,\theta))$ in a vector and W is a weighting matrix.

In light of the above, GMM estimates in EViews are obtained by writing the moment conditions as an orthogonality or moment condition between an expression including the parameters to be estimated and a set of instrumental variables. To estimate an equation by GMM, either create a new equation object by selecting **Object/New Object…/Equation**, go to **Quick/Estimate Equation…** or press the **Estimate** button in the toolbar of an existing equation. In the **Equation Estimation Specification** dialog, go to **Estimation settings, Method** and select **GMM**. The **Equation Estimation Specification** dialog will change to allow you to input the equation to be estimated as well as the instruments you want to use to set up the orthogonality or moment conditions.[12]

Before discussing the results, it is worth reminding ourselves what EViews does when it estimates an equation by GMM. What is the exact set-up of the moment conditions? The first equation we want to estimate is given in column 1 in Table 3 below. The regressors for `ygapsa` can be read off by going down the column. They are a `constant, rpr(-3), ygapsa(-1)` and `ygapagrsa`. The equation to be estimated looks as follows:

$$ygapsa_t = c(1) + c(2)*rpr_{t-3} + c(3)*ygapsa_{t-1} + c(4)*ygapagrsa_t + \varepsilon_t \tag{13}$$

or, re-written in terms of the residuals:

$$\varepsilon_t = ygapsa_t - c(1) - c(2)*rpr_{t-3} - c(3)*ygapsa_{t-1} - c(4)*ygapagrsa_t \tag{14}$$

To obtain GMM estimates in EViews, we must be able to write the moment conditions (11) as an orthogonality condition between the residuals of a regression equation, ε, and a set of instrumental variables, Z. Hence, using equation (14), we set up the (population) orthogonality or moment conditions as $E[Z'\varepsilon] = 0$. The equivalent sample moment conditions are given by:

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[11] At the same time, purely backward-looking specifications can still be estimated by OLS.
[12] For the GMM estimator to be (just) identified, there must be at least as many instruments as there are parameters to estimate.

$$\frac{1}{T}\sum_{t=1}^{T}Z'\varepsilon = 0 \tag{15}$$

or, for the first instrument, which is the constant:

$$\frac{1}{T}\sum_{t=1}^{T}1 \times [ygapsa_t - c(1) - c(2) * rpr_{t-3} - c(3) * ygapsa_{t-1} - c(4) * ygapagrsa_t] = 0 \tag{16}$$

The reason we always include the constant as an instrument is to restrict the model errors in equation (13) to have mean zero. In addition to the sample moment condition (16) for the constant, we also have a sample moment condition generated by the second instrument, `rpr(-1)`:

$$\frac{1}{T}\sum_{t=1}^{T}rpr_{t-1} \times [ygapsa_t - c(1) - c(2) * rpr_{t-3} - c(3) * ygapsa_{t-1} - c(4) * ygapagrsa_t] = 0 \tag{17}$$

There will be 15 more such moment conditions involving `rpr(-2)`, `ygapsa(-1 to -2)`, `ygapagrsa(-1 to -2)`, `wexprgapsa(-1 to -2)`, `reer36gapsa(-1 to -2)`, `dlnfc(-1 to -2)`, `dlbsesa(-1 to -2)` and `crr(-1 to -2)`. In total, we thus have 17 sample moment conditions (which have to be solved simultaneously, which GMM does by minimising the criterion function given in equation (12)).

In two-stage least squares (TSLS) and instrumental variable (IV) estimation, the aim is to use instruments that are uncorrelated with the errors but highly correlated with the regressors. It may therefore strike you as unusual to use `ygapsa(-1)` as an instrument when it is also included in the equation to be estimated. But the definition of an instrument between TSLS and IV estimation on the one hand and GMM estimation on the other differs somewhat. In GMM, any variable in the information set of the agent can be used as an instrument. Note that the choice of instruments is generally arbitrary, in the sense that it often amounts to using only a subset of the information variables. As `ygapsa(-1)` will be known at time t, it falls into the information set and can therefore be used as an instrument.[13]

Following on from above, the first equation in Table 3 we estimate in EViews is:

<center>`ygapsa c rpr(-3) ygapsa(-1) ygapagrsa`</center>

The instrument list used by Patra and Kapur is (see the Notes to Table 1 on page 27 of their paper):

<center>`c rpr(-1 to -2) ygapsa(-1 to -2) ygapagrsa(-1 to -2)`</center>
<center>`wexprgapsa(-1 to -2) reer36gapsa(-1 to -2) dlnfc(-1 to -2)`</center>
<center>`dlbsesa(-1 to -2) crr(-1 to -2)`</center>

Note that for the estimations involving the real policy rate relative to WPI inflation (`rprwpi`) in columns 10 and 11 in Table 3 below, the instruments `rpr(-1 to -2)` are replaced by the instruments `rprwpi(-1 to -2)`.

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[13] In fact, estimating the model with the following instruments (`c`, `rpr(-3)`, `ygapsa(-1)`, `ygapagrsa`), i.e., using the variables that appear in the equation to be estimated as instruments recovers the OLS estimates. This is not surprising as we use the matrix of regressors, X, as the instruments (Z). Recall that we can obtain the OLS estimator as a GMM estimator with the (population) orthogonality conditions: $E[X'\varepsilon] = E[X'(y - X\beta)] = X'(y - X\beta) = 0$. Note that the standard errors will be different from the OLS estimates, as GMM adjusts for heteroskedasticity and serial correlation of unknown form, which OLS does not.

5.1.1 GMM estimation of the dynamic IS curve in EViews 6

On the right-hand side of the **Equation Estimation Specification** dialog are the options for specifying the estimation weighting matrix W in the objective function (12). If you select:

- **Weighting matrix: cross section (White Cov.)**, the GMM estimator will be robust to heteroskedasticity and **contemporaneous** correlation of unknown form; or
- **Weighting matrix: time series (HAC)**, the GMM estimates will be robust to heteroskedasticity and **serial** correlation of unknown form.

If you select the **HAC (Newey-West)** option, you have to specify the kernel type and bandwidth:

- the **Kernel Options** determine the functional form of the kernel used to weight the autocovariances in computing the weighting matrix;
- the **Bandwidth Selection** option determines how the weights given by the kernel change with the lags of the autocovariances in the computation of the weighting matrix (if you select **Fixed** bandwidth, you may either enter a number for the bandwidth or type `nw` to use Newey and West's (1987) fixed bandwidth selection criterion); and
- the **Whitening** option runs a VAR(1) on the variables in the model prior to estimation to 'soak up' the correlation in the moment conditions.

Leave EView's default options for the weighting matrix and kernel choice, which are time series (HAC) and Bartlett. As outlined in footnote 9 in Patra and Kapur (2010, p. 24), the authors use a fixed bandwidth selection with two lags in all cases (with one exception that we will return to below). To make the author's choice operational, we have to enter 2 in the window that currently contains `nw` in the bandwidth selection section of the GMM options. Finally, click on the **Equation Estimation Options** tab and enter 2 for the **Max iterations** option.[14] This tells EViews to iterate the GMM estimates twice, starting with the identity matrix as an initial estimate for W and iterating once more after that. Return to the **Equation Estimation Specification** tab. Once you have entered the equation, the instruments, the sample period and all the other required options as discussed, click **OK**. We get the results in Table 1.

Table 1: GMM estimation results of the dynamic IS curve

Dependent Variable: YGAPSA
Method: Generalized Method of Moments
Sample (adjusted): 1998Q1 2009Q3
Included observations: 47 after adjustments
Kernel: Bartlett, Bandwidth: Fixed (2), No prewhitening
Simultaneous weighting matrix & coefficient iteration
Instrument list: C RPR(-1 TO -2) YGAPSA(-1 TO -2) YGAPAGRSA(-1 TO -2)
    WEXPRGAPSA(-1 TO -2) REER36GAPSA(-1 TO -2) DLNFC(-1 TO -2)
    DLBSESA(-1 TO -2) CRR(-1 TO -2)

	Coefficient	Std. Error	t-Statistic	Prob.
C	0.326197	0.091788	3.553815	0.0009

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[14] Patra and Kapur are not very forthcoming with the technical details of their estimation and simulation procedures. The closest correspondence with their results was achieved by using a two-step iterative GMM procedure.

RPR(-3)	-0.101791	0.034166	-2.979321	0.0047
YGAPSA(-1)	0.607171	0.078414	7.743105	0.0000
YGAPAGRSA	0.127325	0.042753	2.978180	0.0048

R-squared	0.660737	Mean dependent var	0.034830
Adjusted R-squared	0.637067	S.D. dependent var	1.176371
S.E. of regression	0.708692	Sum squared resid	21.59649
Durbin-Watson stat	1.819545	J-statistic	0.263438

For every equation the authors estimate, they also calculate two diagnostic tests, which are:

- the Box-Pierce-Ljung *Q*-statistic for residual autocorrelation up to fourth order (which has a critical value of $\chi^2(4) = 9.49$); and
- Hansen's (1982) *J*-test of over-identifying restrictions.

The Box-Pierce-Ljung *Q*-statistic can be found by going to **View**/**Residual Tests**. Select **Correlogram – Q-statistics** and then four lags. The test statistic is 0.79 with a *p*-value of 0.94, indicating that we cannot reject the null hypothesis of no residual autocorrelation. In other words, we have purged the series of all autocorrelation up to and including fourth order.

Finally, we require the test statistic for Hansen's (1982) *J*-test of over-identifying restrictions. Note that EViews 6 produces the **J-statistic** which allows us to determine whether we have instruments that are **orthogonal to the regressors** (it does not, however, state whether we have weak instruments, which is also potentially important). The *J*-statistic is the minimised value of the objective function at the GMM estimate (equation (12) above), which is not equal to zero (why?). The *J*-test itself is given by multiplying the *J*-statistic reported in EViews 6 times the number of observations, $47 \times 0.263438 = 12.38$. The test is distributed as chi-squared with (*q* - *k*) degrees of freedom, where *q* is the number of instruments and *k* is the number of coefficients to be estimated. In our case, *q* = 17 and *k* = 4, so our test is distributed as $\chi^2(13)$, which has a critical value of 22.36 at the 5 per cent level. Thus, given that four instruments are valid and exactly identify the coefficients, the 13 'extra' instruments are good instruments to use (why?).

Getting the exact probability value for the above *J*-test in EViews 6 requires a little bit of extra work. EViews automatically saves the relevant bits of estimation output data that are needed for calculating the test statistic. We can get the test statistic from above as a named scalar in EViews after estimating an equation by GMM using the following commands in the command window:

```
scalar overid = @regobs*@jstat
scalar overid_p = 1 - @cchisq(overid,13)
```

where `@regobs` is the number of observations (47), `@jstat` is the minimised value of the *J* statistic (0.263438) and `@cchisq(a,b)` calculates the χ^2 distribution of *a* with *b* degrees of freedom. The second command calculates the *p*-value of the test statistic as a named scalar called `overid_p`. To view its value (0.50), double-click on its name: the value will be displayed in the status line at the bottom of the EViews window. The estimation results (the valid over-identifying restriction) suggests that, given our dataset, the dynamic IS cannot be rejected, statistically.

5.1.2 GMM estimation of the IS curve in EViews 7

To estimate an equation by GMM, either create a new equation object by selecting **Object**/**New Object…**/**Equation**, go to **Quick**/**Estimate Equation…** or press the **Estimate** button in the toolbar of an existing equation. In the **Equation Estimation Specification** dialog, go to **Estimation settings, Method** and select **GMM – Generalised Method of Moments**. The **Equation Estimation Specification** dialog will change to allow you to input the equation to be estimated as well as the instruments you want to use to set up the orthogonality or moment conditions. The estimation specification dialog will change as depicted in the screenshot below.
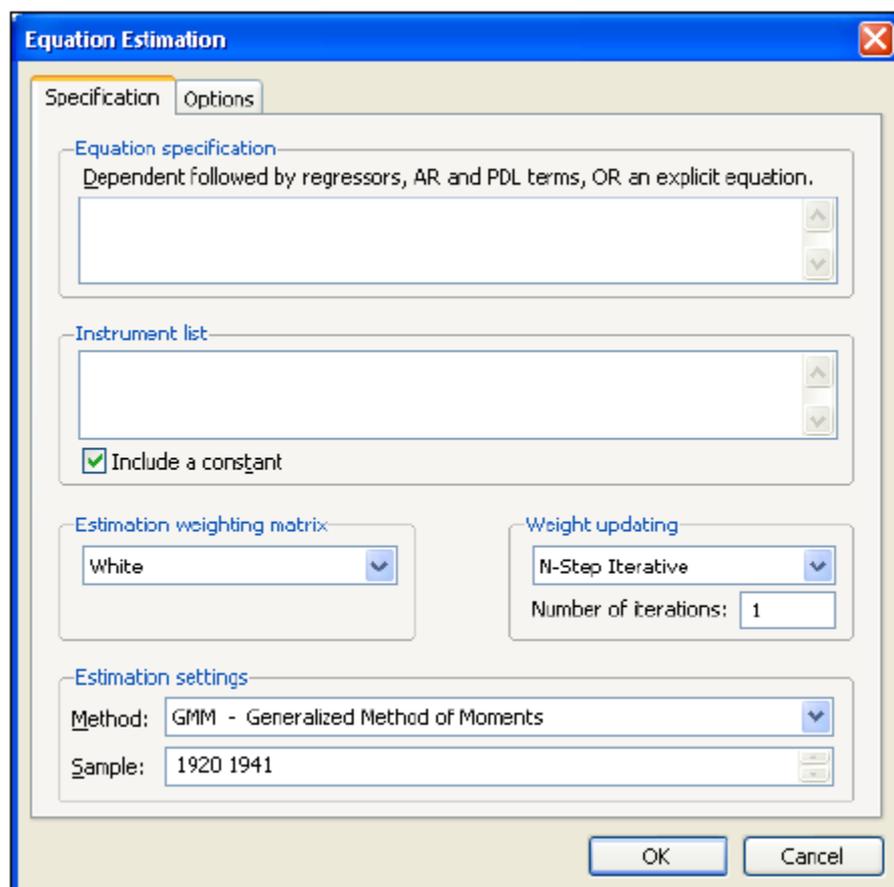
In the middle of the **Equation Estimation Specification** dialog are the options for specifying the estimation weighting matrix W in the objective function (12). EViews 7 offers four methods for specifying an estimation weighting matrix, which are two-stage least squares, White, HAC (Newey-West) and user-specified. In most cases, we should think about employing either White or HAC (Newey-West). If you select:

- **Estimation weighting matrix: White**, the GMM estimator will be robust to heteroskedasticity and **contemporaneous** correlation of unknown form; or
- **Estimation weighting matrix: HAC (Newey-West)**, the GMM estimates will be robust to heteroskedasticity and **serial** correlation of unknown form.

If you select the **HAC (Newey-West)** option, you have to specify the kernel type and bandwidth:

- the **Kernel Options** determine the functional form of the kernel used to weight the autocovariances in computing the weighting matrix;
- the **Bandwidth Selection** option determines how the weights given by the kernel change with the lags of the autocovariances in the computation of the weighting matrix (if you select **Fixed** bandwidth, you may either enter a number for the bandwidth or type `nw` to use Newey and West's (1987) fixed bandwidth selection criterion); and
- the **Whitening** option runs a VAR(p) on the variables in the model prior to estimation to 'soak up' the correlation in the moment conditions. The lag length, p, of the VAR can either be set manually or selected automatically using the standard information criteria (AIC, Schwarz and Hannan-Quinn).

For equations that are linear in their coefficients, EViews 7 offers three updating options for the weighting matrix: **N-step Iterative**, **Iterate to Convergence** and **Continuously Updating**. Somewhat confusingly, EViews regards what is conventionally known as the two-step GMM estimator in the literature as a one-step estimator since there is only a single optimal weighting matrix computation. Selecting **N-step Iterative** and a single iteration therefore replicates the conventional two-step GMM estimator. The remaining two options are pretty self-explanatory.

Updating in EViews 7 is different from EViews 6, which used the identity matrix to form an initial estimate of *W*, after which we could iterate further. In contrast, EViews 7 calculates initial parameter estimates for θ, on the basis of which it then forms residuals, $\varepsilon(\theta)$. It then forms an initial estimate of the long-run covariance matrix, which is then used to compute the optimal weighting matrix, *W*. The GMM objective function (12) is then minimised using this estimate of *W*, which provides updated parameter estimates that can be iterated further.

For equations that are non-linear in their coefficients, EViews 7 offers five updating options for the weighting matrix: **Sequential N-step Iterative**, **Sequential Iterate to Convergence**, **Simultaneous Iterate to Convergence**, **1-Step Weight Plus 1 Iteration** and **Continuously Updating**. The methods for non-linear specifications are generally similar to their linear counterparts, with the differences mainly centring around the fact that the parameter estimates for a given weighting matrix must now be calculated using a non-linear optimiser, which itself involves iteration.

Having estimated the coefficients of the model, we need to specify a method of computing the coefficient variance-covariance matrix. EViews 7 offers six different conventional variance-covariance specifications, which can be found under the **Options** tab in the **Equation Estimation** window: **Estimation default**, **Estimation updated**, **Two-stage Least Squares**, **White**, **HAC (Newey-West)** and **User defined**.

Leave EView's default options for the estimation weighting matrix and kernel choice, which are time series (HAC) and Bartlett. As outlined in footnote 9 in Patra and Kapur (2010, p. 24), the authors use a fixed bandwidth selection with two lags in all cases (with one exception that we will return to below). To make the author's choice operational, click on the **HAC options** button and change the **Bandwidth method** to **User-specified** and enter 2 in the window for **Bandwidth value**. Then, confirm **N-Step Iterative** for the **Weight updating** and select 1 iteration.[15] This actually tells EViews to iterate the GMM estimates twice, starting with a two-stage least squares estimate of the coefficient vector as an initial estimate for *W* and iterating once more after that. Finally, click on the **Options** tab to make sure that we have selected the **Estimation default** option (with the degrees of freedom adjustment) for the **Covariance weighting matrix**. This instructs EViews to use the previously computed estimate of the long-run variance-covariance matrix to form the asymptotic variance-covariance matrix of the coefficient

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[15] Patra and Kapur are not very forthcoming with the technical details of their estimation and simulation procedures. The closest correspondence with their results was achieved by using a two-step iterative GMM procedure.

estimates, θ. Return to the **Equation Estimation Specification** tab. Once you have entered the equation, the instruments, the sample period and all the other required options as discussed, click **OK**. The results are reproduced in Table 2 below. These are the closest results to the numbers in Column 1 of Table 1 in the original paper that I can get.

Table 2: GMM estimation results of the dynamic IS curve

Dependent Variable: YGAPSA
Method: Generalized Method of Moments
Sample: 1998Q1 2009Q3
Included observations: 47
Linear estimation with 1 weight update
Estimation weighting matrix: HAC (Bartlett kernel, User bandwidth = 2.0000)
Standard errors & covariance computed using estimation weighting matrix
Instrument specification: RPR(-1 TO -2) YGAPSA(-1 TO -2) YGAPAGRSA(-1
    TO -2) WEXPRGAPSA(-1 TO -2) REER36GAPSA(-1 TO -2) DLNFC(-1
    TO -2) DLBSESA(-1 TO -2) CRR(-1 TO -2)
Constant added to instrument list

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.362273	0.100708	3.597278	0.0008
RPR(-3)	-0.110246	0.036856	-2.991241	0.0046
YGAPSA(-1)	0.592928	0.082829	7.158447	0.0000
YGAPAGRSA	0.141627	0.049037	2.888139	0.0060

R-squared	0.662696	Mean dependent var	0.034830
Adjusted R-squared	0.639163	S.D. dependent var	1.176371
S.E. of regression	0.706642	Sum squared resid	21.47177
Durbin-Watson stat	1.769335	J-statistic	11.46945
Instrument rank	17	Prob(J-statistic)	0.571553

As can be seen from the output in EViews 7, the new version of EViews automatically calculates the *p*-value of the *J*-statistic, which is equal to 0.57. The other new bit of information that has been added to EViews 7 is the instrument rank, which gives the number of linearly independent instruments used in estimation (here equal to 17).

All the other alternative specifications of the IS curve in columns 1 through 11 of Table 3 below are estimated accordingly (using EViews 7), with the exception of column 9, which contains backward-looking data only. For that reason, this specification can be estimated using OLS (with HAC-adjusted standard errors to allow for comparison across estimation techniques).

Variable	Alternative specifications										
	1	2	3	4	5	6	7	8	9 (OLS)	10	11
	Dependent variable: `ygapsa`										
	Using GDP deflator									Using WPI	
constant	0.36 (3.60)	0.40 (4.16)	0.35 (3.83)	0.23 (1.87)	0.02 (0.17)	0.11 (1.11)	0.12 (1.27)	0.05 (0.47)	0.18 (1.08)	0.08 (0.85)	-0.02 (-0.25)
rpr(-3)	-0.11 (-2.99)		-0.13 (-3.75)								
rpr(-5)						-0.05 (-1.32)		-0.03 (-0.71)	-0.09 (-1.71)		
rpr(-6)				-0.11 (-2.51)			-0.06 (-1.56)				
rpr(-7)					-0.02 (-0.36)						
rpr(-8)		-0.16 (-4.23)									
rprwpi(-5)										-0.01 (-0.25)	-0.02 (-0.70)
ygapsa(-1)	0.59 (7.16)	0.41 (7.00)	0.28 (3.60)			0.39 (5.52)	0.38 (5.79)	0.22 (2.63)	0.27 (2.52)	0.30 (3.32)	0.27 (4.03)
ygapsa(+1)				0.58 (7.79)	0.36 (5.37)	0.41 (4.82)	0.40 (5.67)	0.32 (3.39)			0.51 (4.61)
ygapagrsa	0.14 (2.89)	0.23 (6.33)	0.22 (4.67)	0.23 (5.44)	0.25 (7.30)	0.13 (2.79)	0.13 (2.95)	0.20 (3.89)	0.25 (11.87)	0.26 (4.86)	0.13 (2.82)
wexprgapsa			0.11 (6.62)		0.10 (6.51)			0.06 (3.20)	0.08 (2.81)	0.09 (5.37)	0.03 (1.64)
reer36gapsa(-2)			-0.06 (-2.47)		-0.02 (-0.78)			-0.02 (-0.72)	-0.08 (-2.46)	-0.07 (-3.05)	0.00 (-0.13)
SEE	0.71	0.64	0.62	0.67	0.54	0.55	0.55	0.50	0.54	0.66	0.60
R-bar squared	0.64	0.73	0.72	0.70	0.81	0.80	0.80	0.83	0.80	0.69	0.75
Q-statistic	0.94	0.85	0.26	0.76	0.96	0.01	0.02	0.20	0.75	0.75	0.03
J-test	11.47	10.98	9.85	12.32	7.76	11.58	10.57	5.29		14.26	5.47
Significance level of *J*-test	0.57	0.61	0.54	0.50	0.73	0.48	0.57	0.87		0.22	0.86

Notes: Estimation is by the generalised method of moments (GMM) over the sample period 1997 Q2 to 2009 Q3 using quarterly data and two lags each of the following instruments: `rpr`, `ygapsa`, `ygapagrsa`, `wexprgapsa`, `reer36gapsa`, `dlnfc`, `dlbsesa` and `crr`. In specifications 10 and 11, the instrument `rpr` is replaced by `rprwpi`. Standard errors have been corrected using the Newey-West/Bartlett window with two lags. Specification 9 is estimated by OLS. Variable names are given in Appendix 1. Figures in parentheses are *t*-statistics. The *Q*-statistic gives the significance level of the Box-Pierce-Ljung *Q*-statistic for residual autocorrelation up to four lags. The *J*-test and its significance level is a test of the overidentifying restrictions. SEE is the standard error of the estimate.

In the baseline backward-looking IS curve (column 1), we find the expected theoretical result, namely that the real policy interest rate (`rpr`) has a (lagged) negative impact on the output gap (`ygapsa`): a 1 percentage point increase in the real policy interest rate leads to a narrowing of the output gap by 0.11 percentage points with a delay of three quarters, reflecting the lags inherent in the Indian monetary transmission mechanism.[16]

We also find that the coefficient on the (seasonally-adjusted) agricultural GDP gap (`ygapagrsa`) is positive and significant, indicating that fluctuations in agricultural activity relative to trend have a significant positive effect on the Indian economy (notwithstanding the rising prominence of services

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[16] The long-run coefficient is equal to -0.11/(1 − 0.59) = -0.27, i.e., almost three times as large.

within the Indian economy). In fact, `ygapagrsa` is statistically significant in all eleven estimated models. The diagnostic test for residual serial correlation in column 1 indicates that there is no serial correlation up to fourth order. We can see that this absence of serial correlation applies to all but three of the estimated equations in this exercise. Note that for reasons outlined in Patra and Kapur (2010, p. 25), lags of the real interest rate remain significant beyond three quarters – at least up to eight quarters in the baseline backward-looking specification of the IS curve (with all the other variables remaining statistically significant). This can be seen from column 2 in Table 3.

Column 3 in Table 3 looks at the effects of incorporating variables representing external demand on the Indian output gap. Two measures in particular are included. The first proxy for external demand conditions is the (seasonally-adjusted) real world export gap (`wexprgapsa`), which is statistically significant: a 1 percentage increase in the real world export gap leads to a contemporaneous 0.11 percentage point increase in the Indian output gap in the short-run, with a long-run impact of $0.11/(1 – 0.28) = 0.16$ percentage points. The second variable, the (seasonally-adjusted) real appreciation of the exchange rate gap (`reer36gapsa`), has the expected negative effect: an appreciation of 1 percentage point in the real exchange rate gap leads to a narrowing of the output gap of 0.06 percentage points with a lag of two quarters.

As a result of augmenting the baseline specification with the two proxies of external demand, the coefficient on the real interest rate has increased in magnitude to -0.13 from -0.11.

The (absolute) sum of the coefficients on the real interest rate and the real exchange rate is equal to 0.19 (0.26 in the long-run), in line with the cross-country finding of 0.10 to 0.25 for quarterly models in Berg *et al.* (2006). The results are qualitatively unchanged when estimating the backward-looking specification by OLS rather than GMM (as done in column 9), even though the real policy interest rate variable enters significantly only at the fifth lag – and only at the 10 per cent level of significance.

In terms of the forward-looking specification of the IS curve, we again estimate both the baseline and the augmented specification (columns 4 and 5 respectively). While the results for the baseline specification of the IS curve in column 4 are broadly the same as for the backward-looking specification, the real policy interest rate only enters significantly at the sixth lag. Moreover, there is no support for the augmented forward-looking specification as the (seventh lag of the) real policy interest rate is not significant (column 5).

The baseline hybrid specifications that include both lagged and expected output gaps can be found in columns 6 and 7. Specifying the model in this form finds empirical support, in the sense that the coefficients on both the lagged and the one-quarter-ahead expected output gap are positive and significant – with the coefficient on expected output being somewhat higher than for the lagged output gap. At the same time, the coefficient on the real policy interest rate is significant at the fifth and sixth lag only. We should also note the significant residual serial correlation up to fourth order in both specifications.

When the hybrid specification in column 6 is augmented to control for the two external demand variables, world real export growth and the lagged real exchange rate gap, the coefficient on the real policy interest rate becomes insignificant (column 8), which is just as in the augmented forward-looking model in column 5.

Using wholesale price index inflation (`infwpi`) rather than the GDP deflator, the coefficient on the (lagged) real policy interest rate is still correctly signed, although no longer statistically significant (columns 10 and 11). Patra and Kapur assign this empirical finding to the greater variability in quarter-on-quarter headline WPI inflation. Other estimated coefficients using the real policy interest rate deflated by WPI inflation remain broadly unchanged from those based on the GDP deflator. The hybrid specification in column 11, which includes both lagged and expected output gaps as well as the two external demand variables, does not seem to be a good model: `wexprgapsa` and `reer36gapsa(-2)` are insignificant and the regressions suffers from residual autocorrelation.

The authors conclude that the backward-looking augmented specification (column 3) provides the best fit and is therefore their preferred specification. We will assess this claim in Section 5.6.

5.2 The new Keynesian Phillips curve

The limited empirical evidence for Phillips curves estimated on Indian data, most recently discussed in Patra and Ray (2010), generally supports a backward-looking specification. As a result, the purely backward-looking specification of the Phillips curve in column 1 of Table 4 is chosen as the benchmark model. The empirical results of the benchmark model indicate that a 1 percentage point increase in the (seasonally-adjusted) output gap (`ygapsa`) results in a 0.31 percentage point increase in inflation as measured by the GDP deflator (`infgdp`) four quarters later.[17] In addition, inflation displays a considerable degree of inertia: the lagged autoregressive coefficient of 0.66 is large and statistically significant, indicating that shocks to inflation can be persistent. Global non-fuel commodity prices (`infglobal`) have the expected positive impact on domestic inflation. The small size of the estimated coefficient (0.06 in the short run and 0.17 in the long-run) has to be seen in relation to the much greater variability of global (non-fuel) commodity prices. Figure 2 illustrates the volatility of global (non-fuel) commodity price inflation: in the sample period, this measure of inflation varied between 10 and 20 per cent on the plus side and 40 per cent on the minus side.

Figure 2: Year-on-year global non-fuel commodity price inflation (`infglobal`) and primary article inflation (`infpc`)
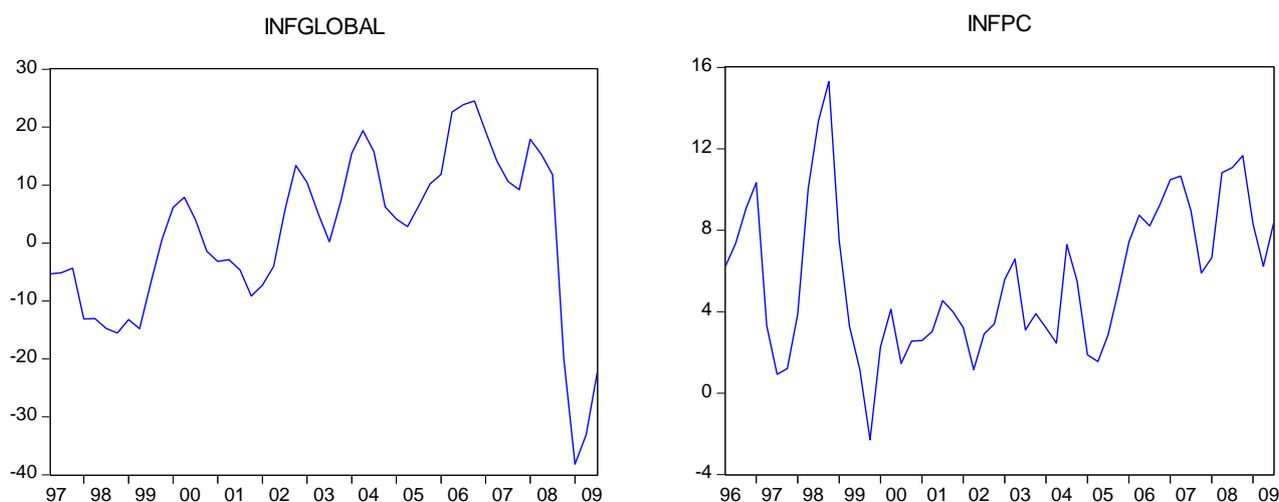
Assume a quarterly change in `infglobal` of 15 per cent, as was the case in 2008 Q2. The estimated coefficient of 0.06 suggests that this increase in global commodity prices would have added almost 0.85 percentage points to domestic inflation in the same quarter. Similarly, in 2009 Q1, global commodity prices fell by slightly more than 38 per cent. The estimated same-quarter effect on domestic inflation would have been a reduction of almost 2.2 percentage points (with domestic inflation at that point running at 2 per cent). We can therefore conclude that the significant volatility imparted by global commodity prices has been an important driver of domestic inflation in the latter half of the estimation sample.[18] Again, as in the case of `ygapagrsa` in the IS curve, the volatility of exogenous variables such

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[17] The long-run impact is three times higher at $0.31/(1 - 0.66) = 0.90$ percentage points (or 90 basis points).

[18] An accompanying exercise on simulating the – estimated – monetary policy model (without money) for India assesses this claim in more detail.

as `infglobal` in the new Keynesian Phillips curve will play an important role when assessing the fit of the NK model.

Note that the OLS estimates for the backward-looking specification in column 7 of Table 4 are fairly similar to the GMM estimates in column 1 in Table 4. In light of the sharp acceleration in the `infpc` measure of primary articles inflation from 1.2 per cent in the final quarter of 1997 to 15.3 per cent a year later (Figure 2), the authors included a dummy (`dum1998q3q4`) that takes a value of one for the third and fourth quarters of 1998.[19] Estimation results for all the alternative specifications of the new Keynesian Phillips curve are reproduced in Table 4.

Table 4: Estimates of alternative specifications of the new Keynesian Phillips curve

Variable	Alternative specifications									
	1	2	3	4	5	6	7 (OLS)	8 (OLS)	9	10
	Dependent variable: `infgdp`								Dependent variable: `infwpi`	
	Sample period: 1997:2 – 2009:3									
constant	1.19	1.88	1.02	0.01	-0.02	-0.18	1.05	0.98	1.14	-1.11
	(7.62)	(7.06)	(5.21)	(0.03)	(-0.07)	(-0.76)	(3.60)	(3.84)	(5.35)	(-3.72)
ygapsa(-4)	0.31	0.34	0.18	0.22	0.18	0.12	0.24	0.19	0.21	0.01
	(4.12)	(3.29)	(1.90)	(3.15)	(2.17)	(1.69)	(2.28)	(1.81)	(1.57)	(0.11)
infgdp(-1)	0.66		0.67	0.60	0.58	0.59	0.69	0.67		
	(19.95)		(17.12)	(12.53)	(12.95)	(13.47)	(8.90)	(11.04)		
infgdp(+1)		0.55		0.36	0.37	0.41				
		(10.89)		(7.57)	(6.65)	(8.88)				
infwpi(-1)									0.66	0.62
									(16.28)	(18.99)
infwpi(+1)										0.59
										(10.81)
infglobal	0.06		0.07	0.03	0.03	0.03	0.06	0.08	0.09	0.02
	(11.55)		(5.19)	(4.12)	(2.38)	(2.34)	(3.55)	(2.86)	(5.93)	(1.39)
dum1998q3q4	4.02	2.86	3.56	1.70	1.28		4.23	3.89	2.08	0.43
	(8.16)	(3.19)	(3.31)	(1.66)	(1.14)		(11.98)	(8.41)	(3.52)	(0.81)
dlexcha			0.05		0.02	0.03		0.05	0.05	0.03
			(1.63)		(0.97)	(1.34)		(1.36)	(1.69)	(1.32)
SEE	1.08	1.30	1.06	0.91	0.91	0.97	1.07	1.05	1.01	0.75
R-bar squared	0.71	0.56	0.72	0.79	0.79	0.76	0.72	0.73	0.74	0.85
Q-statistic	0.29	0.06	0.37	0.02	0.01	0.01	0.32	0.43	0.01	0.00
J-test	14.86	16.78	15.12	15.03	16.33	16.95			16.10	13.07
Significance level of *J*-test	0.54	0.47	0.44	0.45	0.29	0.32			0.38	0.52
Chi-squared(1)				0.40	0.46	0.01				8.91
Significance level				0.53	0.50	0.94				0.00
Sacrifice ratio	1.11		1.80				1.29	1.69	1.59	
Exchange-rate pass-through (long-run coefficient)			0.14					0.15	0.15	

Notes: Estimation is by the generalised method of moments (GMM) over the sample period 1997 Q2 to 2009 Q3 using quarterly data and two lags each of the following instruments: `ygapsa`, `ygapagrsa`, `infgdp`, `infcpi`, `infwpi`, `infglobal`, `infpc`, `infpol`, `dlexcha` and `dlm3`. In columns 9 and 10, the dependent variable `infgdp` is replaced by `infwpi`. Columns 7 and 8 are estimated by OLS. Variable names are given in Appendix 1. Figures in parentheses are *t*-

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[19] The `infpc` measure of inflation forms a sub-group within the wholesale price inflation measure.

statistics. The *Q*-statistic gives the significance level of the Box-Pierce-Ljung *Q*-statistic for residual autocorrelation up to four lags. The *J*-test and its significance level is a test of the overidentifying restrictions. The sacrifice ratio is defined as ((1 – coefficient on lagged inflation)/coefficient on output gap). SEE is the standard error of estimate. The $\chi^2(1)$ statistic and its associated significance level tests the null hypothesis that the sum of the coefficient on lagged and expected inflation is equal to one.

The estimated equations imply a sacrifice ratio, defined as ((1 – coefficient on lagged inflation)/coefficient on output gap) of between 1.0 and 1.8, which is in line with earlier estimates by the same authors for India in Kapur and Patra (2000). In consequence, a monetary policy-induced disinflation of one percentage point from its trend or long-run average is associated with a reduction of between 1.0-1.8 per cent in output.

We can also use the empirical results in Table 4 to assess the question of whether the inflationary process in India is forward-looking, and there is some support for this proposition from the results. In the purely forward-looking specification in column 2 of Table 2, the coefficient on the lagged output gap (`ygapsa(-4)`) is significant and broadly unchanged relative to the backward-looking specification in column 1. The statistically significant coefficient on lead inflation (`infgdp(+1)`) of 0.55 underscores the importance of inflation expectations in influencing the current level of inflation. The hybrid Phillips curve specification in column 4 has statistically significant coefficients on both one-period lagged (0.60) and one-quarter-ahead inflation (0.36). The magnitude of these coefficients is again consistent with the cross-country evidence in Berg *et al.* (2006), who find coefficients on expected inflation to be markedly below 0.50. The coefficient on the output gap (`ygapsa(-4)`) is still significant, albeit equal to 0.22 rather than the value of 0.31 in the benchmark specification of column 1. In order to validate the vertical nature of the long-run Phillips curve, we can test the null hypothesis that the sum of the coefficients on one-period lagged and one-quarter-ahead expected inflation is equal to one. With probability values (well) above 0.05, the null hypothesis cannot be rejected for two of the three models involving the GDP deflator as the inflation measure in columns 4, 5 and 6.

For open economies, the exchange-rate pass through into domestic inflation is of great interest, especially in light of increasing globalisation, the concomitant greater co-movement of global and domestic prices as well as the greater volatility of the exchange rate. While the IMF (2010) advocates using the exchange rate as an instrument for inflation management in India, RBI governor Subbarao (2010) made it clear that Indian exchange-rate policy was not guided by a fixed or pre-announced exchange-rate target or band. RBI policy has been to '...intervene in the market to manage excessive volatility and disruptions to the macroeconomic situation (p. 913)'. This debate in the Indian context is assessed by augmenting the baseline and hybrid specifications with a nominal exchange rate variables, in this case the year-on-year variation of the Indian rupee versus the US dollar (`dlexcha`).

Looking first at the backward-looking specification in column 3 of Table 4, we find that the exchange-rate variable is statistically significant, although the coefficient on the output gap has fallen to 0.18 from 0.31 in the baseline specification. The dynamics show that the cumulative pass-through increases from 0.05 on impact to $(1 + 0.67) \times 0.05 = 0.08$ after one quarter, $(1 + 0.67 + 0.67^2) \times 0.05 = 0.11$ after two quarters, $(1 + 0.67 + 0.67^2 + 0.67^3) \times 0.05 = 0.12$ after three quarters, $(1 + 0.67^2 + 0.67^3 + 0.67^4) \times 0.05 = 0.13$ after four quarters and so on. The long-run value of exchange-rate pass-through is $0.05/(1 - 0.67) = 0.14$. These results suggest that a 10 per cent appreciation (depreciation) of the Indian rupee (against the US dollar) would reduce (increase) inflation by 0.5 percentage points in the current quarter, by 1.3 percentage points after a year and by 1.4 percentage points in the long run. The coefficient estimates obtained in the hybrid specification in column 6 point to broadly the same results, although the *Q*-statistic indicates significant residual serial correlation up to and including the fourth order. In the OLS estimation of the backward-looking version of the Phillips curve (column 8), the exchange-rate variable is not significant.

Again, we can use the wholesale price index (WPI) as an alternative measure of inflation. Note that in estimating the specification in columns 9 and 10, Patra and Kapur use a fixed bandwidth of 4, rather than the two lags that are used in all the other GMM estimations. Using `infwpi` in place of `infgdp` does not materially alter the results in the backward-looking specification in column 9. At 0.05 in the same quarter and 0.15 in the long run, exchange-rate pass-through is slightly higher. The hybrid version in column 10 does not provide a good fit as the coefficients on the lagged output gap as well as the exchange rate are insignificant. In addition, there is significant residual autocorrelation in both models, and we can reject the null hypothesis of a vertical long-run Phillips curve in column 10.

Overall, the authors conclude, based on a careful assessment of the various specifications and their associated diagnostics, that the backward-looking specification augmented with both the exchange rate and global inflation (Table 4, column 3) is their preferred specification when they simulate the model.

5.3 Monetary policy reaction function or Taylor rule

It is well known that the monetary policy transmission mechanism operates with a long and variable lag. The literature on the monetary policy reaction function therefore expresses a clear preference for a forward-looking rule. As a result, we start with estimates of a forward-looking specification (column 1 in Table 5). Inflation in this context is measured by the deviation of the GDP deflator and WPI inflation from the RBI's indicative inflation projection of 5 per cent (denoted by `infgdpdev` and `infwpidev` respectively). All the other alternative estimation results can be found in Table 5.

Table 5: Alternative estimates of the (forward-looking) monetary policy reaction function

Variable	Alternative specifications							
	1	2	3	4	5	6	7	8
	Dependent variable: `effective3`							
	Inflation measured by GDP deflator				Inflation measured by WPI			
constant	1.35	1.44	1.15	1.51	0.70	0.88	0.73	1.02
	(3.97)	(4.09)	(3.62)	(4.87)	(2.27)	(2.55)	(2.57)	(3.23)
infgdpdev(+2)	0.27	0.23	0.19	0.20				
	(3.00)	(2.36)	(3.36)	(2.73)				
infwpidev(+2)					0.22	0.20	0.18	0.15
					(3.01)	(2.43)	(2.35)	(2.00)
ygapsa(+2)	0.24	0.23	0.03	0.06	0.17	0.17	0.08	0.09
	(2.99)	(2.75)	(0.31)	(0.69)	(2.02)	(1.91)	(0.86)	(0.99)
effective3(-1)	0.79	0.78	0.72	0.67	0.88	0.85	0.82	0.77
	(15.70)	(14.91)	(13.96)	(11.51)	(19.13)	(16.71)	(12.72)	(10.99)
dlexch4(-1)		0.02		0.02		0.01		0.01
		(1.87)		(1.79)		(1.30)		(1.13)
fedtarget			0.20				0.09	
			(3.15)				(1.23)	
fedtarget(-1)				0.19				0.10
				(2.50)				(1.34)
SEE	0.81	0.81	0.68	0.72	0.71	0.73	0.68	0.70
R-bar squared	0.77	0.77	0.84	0.82	0.82	0.81	0.84	0.83
Q-statistic	0.80	0.73	0.38	0.38	0.68	0.72	0.49	0.54
J-test	9.96	6.14	10.79	7.39	8.75	7.22	9.13	7.82
Significance level of *J*-test	0.27	0.52	0.15	0.29	0.36	0.41	0.24	0.25
Long-run coefficient on inflation	1.31	1.02	0.70	0.61	1.78	1.31	1.00	0.68
Long-run coefficient on	1.18	1.04			1.38	1.12	0.45	0.40

output gap					
Long-run coefficient on exchange rate		0.09			
Natural policy rate	6.50	6.49		5.62	5.89

Notes: Estimation is by the generalised method of moments (GMM) over the sample period 1997 Q2 to 2009 Q3 using quarterly data and one lag each of the following instruments: `effective3`, `ygapsa`, `wexprgapsa`, `infgdpdev`, `infcpidev`, `infwpidev`, `infglobal`, `dlexch4`, `dlm3`, `dlnfc` and `fedtarget`. Variable names are given in Appendix 1. Figures in parentheses are *t*-statistics. The *Q*-statistic gives the significance level of the Box-Pierce-Ljung *Q*-statistic for residual autocorrelation up to four lags. The *J*-test and its significance level is a test of the overidentifying restrictions. SEE is the standard error of the estimate.

The authors experimented with a number of leads in the specification in column 1, but concluded that the best results were obtained for a model with two-quarter-ahead inflation and the two-quarter-ahead output gap. Both variables are statistically significant and have the expected sign. In particular, a 1 percentage point increase each in expected inflation and the expected output gap leads to an increase in the policy rate by 27 and 24 basis points respectively. The lagged coefficient on the policy interest rate is 0.79, indicating a high degree of interest-rate smoothing in India, which is consistent with other empirical findings in both advanced and developed economies. The long-run coefficient on inflation is equal to $0.27/(1 - 0.79) = 1.31$. The coefficient in excess of unity is consistent with the Taylor principle, which is a requirement for the monetary policy reaction function to be stable. The long-run coefficient on the output gap is $0.24/(1 - 0.79) = 1.18$, indicating the commitment of the RBI to output stabilisation (within its multiple objectives).[20]

The forward-looking monetary policy reaction function can also be augmented to make it consistent with an open-economy specification. In particular, we include the (lagged) change in the exchange rate of the Indian rupee against the US dollar (`dlexch4`) in column 2 and the US federal funds target rate (`fedtarget`) in column 3.

Both variables turn out to be statistically significant with the expected sign.[21] We find that a 10 per cent depreciation of the Indian rupee against the US dollar, where the exchange rate change is measured as the annualised quarter-on-quarter exchange-rate change, is associated with a modest increase of 2 basis points in the policy rate after a lag of one quarter, *ceteris paribus*. The long-run impact of $0.02/(1 - 0.78) = 0.09$ is less than 10 basis points. The significance level of 0.07 on the `dlexch4(-1)` coefficient estimate may be due to the fact that the Indian rupee has exhibited significant volatility over the sample period. In addition, there is no evidence of any systematic policy rate response to exchange-rate movements since the start of 2000. According to Mohan and Kapur (2009), the RBI has instead used active capital account management as the main instrument to smooth excessive exchange rate volatility in the foreign-exchange market – along with interventions.

In fact, the weight on inflation is almost 12 times that on the exchange rate in the estimated monetary policy rule in column 2, indicative of the fact that the RBI places a lot more importance on reducing inflation volatility than on stabilising exchange-rate changes. Furthermore, the exchange rate coefficient is small and insignificant in all specifications where it is included. In contrast, the coefficient on the output gap is significant in specifications that do not also include the US federal funds target rate. The authors conclude that output stabilisation is an important determinant of the monetary policy response in India.

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[20] International evidence for the six major advanced economies is provided in Clarida *et al.* (1998), who found long-run coefficients on the output gap ranging from 0.08 for Japan to 0.88 for France – with the simple average being 0.36. Blattner and Margaritov (2010) report an average output growth coefficient of 0.94 for the euro-area. Finally, Mohanty and Klau (2004) estimated the long-run coefficient on the output gap in a sample of 13 emerging market economies. The range of estimates went from 0.43 in India to 3.50 in Brazil, with a simple average across the countries of the sample of 1.21.

[21] Note that the exchange rate is only significant at the 10 per cent level.

Turning to the US federal funds target rate, an increase of 100 basis points in the federal funds target rate is associated with a contemporaneous 20 basis point increase in the policy rate (column 3). But we should note that the introduction of `fedtarget` into the equation lowers the long-run effect of inflation to below unity (0.19/(1 − 0.72) = 0.70), which generates instability in the monetary policy reaction function as the Taylor principle no longer holds. We also note that the coefficient on the expected output gap (`ygapsa(+2)`) is no longer statistically significant. Results are qualitatively unchanged when we include the first lag of the federal funds target rate, as can be seen from column 4.

The model can also be specified using WPI inflation (`infwpidev`) rather than the GDP deflator (`infgdpdev`). Results for this specification can be found in columns 5 through 8. In general, the policy response is more robust to inflation and the output gap across all specifications. In the benchmark model in column 5, the long-run coefficient on inflation increases to 1.78. In fact, the long-run coefficient remains above unity in all but one of the specifications involving `infwpidev` – the exception being column 8, where the long-run coefficient drops to 0.68. But we do note some differences *vis-à-vis* the monetary policy reaction function that uses the GDP deflator:

- both the exchange rate change and the US federal funds target rate are insignificant; and
- the degree of interest rate smoothing appears higher, as can be seen from the larger coefficients on `effective3(-1)`.

Without wanting to generalise from the estimation results obtained so far, it may not be recommendable to include an international monetary policy interest rate such as the US federal funds target rate into the monetary policy reaction function for India.

The authors' preferred specification – based on a comparison of various models and diagnostics, including the forecasting performance in Table 7 below – is the model using the GDP deflator and augmented with the exchange rate (Table 5, column 3).

5.4 The natural policy rate

In a monetary policy framework that uses the (short-term) interest rate as the main instrument of policy, an important issue for monetary policymakers is the natural policy rate. In fact, Woodford (2003) stresses that 'Such an approach to policy would make the natural rate of interest a key concept in monetary policymaking (p. 287).' Theoretically, the natural rate corresponds to the policy rate that would prevail with a zero output gap and inflation at its – implicit or explicit – target. This definition implies that when the actual interest rate is at its natural level and is expected to remain there in future, output will also be at its natural level (such that the output gap is zero).

The estimated monetary policy reaction functions in Table 5 implicitly suggest that the natural policy rate is around 5.6 to 6.5 per cent – around 6.5 per cent when the GDP deflator is used and around 5.7 per cent with the WPI measure of inflation.[22] It is worth keeping in mind that we should not treat these estimates as definite point estimates of the natural policy rate pertaining to the Indian economy. As always, these estimates should be corroborated by alternative methodologies. In addition, for many fast-growing emerging market economies, the rate of potential output growth is steadily increasing over time, as more latent productive capacity gets utilised in the domestic economy. In light of these uncertainties, the confidence intervals around natural policy rate estimates might be quite substantial.

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[22] The natural policy rate is calculated as the estimated constant of the regression equation divided by one minus the estimated coefficient on `effective3(-1)`.

5.5 The Taylor rule with contemporaneous variables

The Taylor rule is traditionally specified in terms of contemporaneous variables.[23] Table 6 therefore shows estimates of the monetary policy reaction function with contemporaneous rather than expected values. The baseline specification in column 1 shows that the coefficients on both inflation (infgdpdev) and the output gap (ygapsa) remain positive and significant. We note, however, that the long-run coefficient on inflation now falls below unity, violating the Taylor principle for stability of the monetary policy reaction function, while the long-run coefficient on the output gap remains above one. Including the change in the exchange rate variable into the augmented versions of the benchmark model has no effect: the estimated coefficients in columns 2, 4, 6 and 8 are very small and insignificant throughout. Turning to the US federal funds target rate, the foreign interest rate enters significantly into the specifications involving inflation measured by the GDP deflator (columns 3 and 4), but insignificantly when inflation is measured by the wholesale price index (columns 7 and 8). Quantitatively, the results are roughly unchanged when WPI is used as the measure of inflation (columns 5 through 8).

Table 6: Alternative estimates of the contemporaneous monetary policy reaction function

Variable	Alternative specifications							
	1	2	3	4	5	6	7	8
	Dependent variable: effective3							
	Inflation measured by GDP deflator				Inflation measured by WPI			
constant	1.38	1.73	1.38	1.77	1.30	1.67	1.20	1.56
	(3.97)	(3.49)	(3.38)	(3.86)	(4.14)	(3.81)	(3.03)	(3.46)
infgdpdev	0.11	0.13	0.10	0.12				
	(2.03)	(2.24)	(2.30)	(2.43)				
infwpidev					0.10	0.11	0.07	0.08
					(2.63)	(2.92)	(1.51)	(1.55)
ygapsa	0.29	0.35	0.16	0.17	0.31	0.37	0.21	0.25
	(2.57)	(2.74)	(1.76)	(1.62)	(2.69)	(2.93)	(1.62)	(1.57)
effective3(-1)	0.78	0.73	0.70	0.63	0.78	0.73	0.74	0.70
	(14.01)	(9.67)	(9.74)	(7.91)	(14.93)	(10.49)	(12.10)	(10.58)
dlexch4(-1)		0.01		0.01		0.02		0.01
		(0.99)		(0.80)		(1.34)		(1.07)
fedtarget			0.16				0.12	
			(2.73)				(1.59)	
fedtarget(-1)				0.18				0.10
				(2.40)				(0.90)
SEE	0.69	0.72	0.62	0.64	0.71	0.76	0.67	0.72
R-bar squared	0.84	0.83	0.87	0.87	0.83	0.81	0.85	0.83
Q-statistic	0.96	0.87	0.79	0.82	0.96	0.89	0.83	0.92
J-test	8.42	6.57	10.64	9.12	8.62	5.50	11.03	8.04
Significance level of *J*-test	0.39	0.48	0.16	0.17	0.38	0.60	0.14	0.23
Long-run coefficient on inflation	0.49	0.46	0.33	0.33	0.46	0.42	0.25	0.26
Long-run coefficient on output gap	1.32	1.29	0.54		1.42	1.38	0.81	
Natural policy rate	6.28	6.41			6.02	6.18		

Notes: Estimation is by the generalised method of moments (GMM) over the sample period 1997 Q2 to 2009 Q3 using quarterly data and one lag each of the following instruments: effective3, ygapsa, wexprgapsa, infgdpdev,

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[23] In light of the uncertainty attached to future projections, Taylor (1993) preferred the use of current-period inflation and the current-period output gap rather than their expected future values.

`infcpidev`, `infwpidev`, `infglobal`, `dlexch4`, `dlm3`, `dlnfc` and `fedtarget`. Variable names are given in Appendix 1. Figures in parentheses are *t*-statistics. The *Q*-statistic gives the significance level of the Box-Pierce-Ljung *Q*-statistic for residual autocorrelation up to four lags. The *J*-test and its significance level is a test of the overidentifying restrictions. SEE is the standard error of the estimate.

5.6   Finding the best specification

In order to replicate Table 2 in the original paper by Patra and Kapur (2010, p. 28), it is advantageous to remind ourselves of how to forecast in EViews.

To begin with, once we have estimated the parameters of the system of equations, we may wish to forecast (future) values from a particular equation. We will start with the preferred specification of the IS curve. Re-estimate the dynamic IS curve given in column 3 in Table 3. To get an initial feel for the fit of the model, select **View/Actual, Fitted, Residual...** and select **Actual, Fitted, Residual Graph**. The actual, fitted and residuals for the baseline dynamic IS curve are shown in Figure 3.

Figure 3: Actual, fitted and residuals for the baseline dynamic IS curve
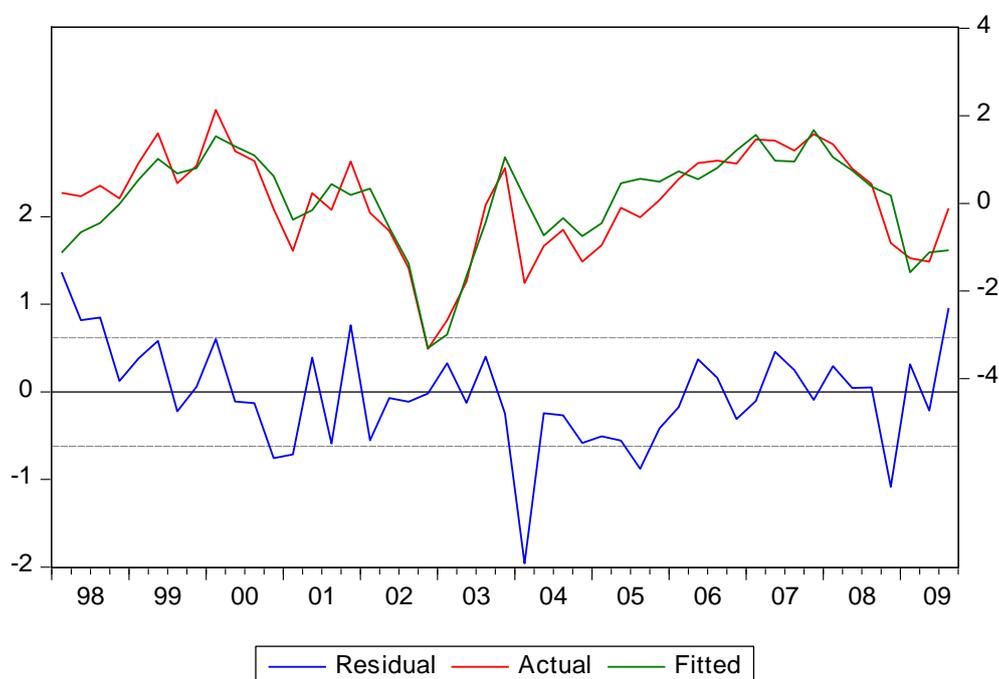
The actual and fitted values depicted on the upper portion of the graph show a general co-movement between the actual value of `ygapsa` and the fitted values of `ygapsa` from the preferred specification estimated by GMM. But note that there are distinct periods where the two series diverge. For much of the period from 2004 to 2005, for instance, the actual value of `ygapsa` consistently lies below its fitted value.

To forecast `ygapsa` from this equation (either in- or out-of-sample), click on the **Forecast** button on the equation toolbar. Alternatively, you can select **Proc/Forecast...**.

At the top of the **Forecast** dialog, EViews displays information about the forecast: in this case, we are forecasting values for the dependent series `ygapsa` using an estimated, but untitled, equation.

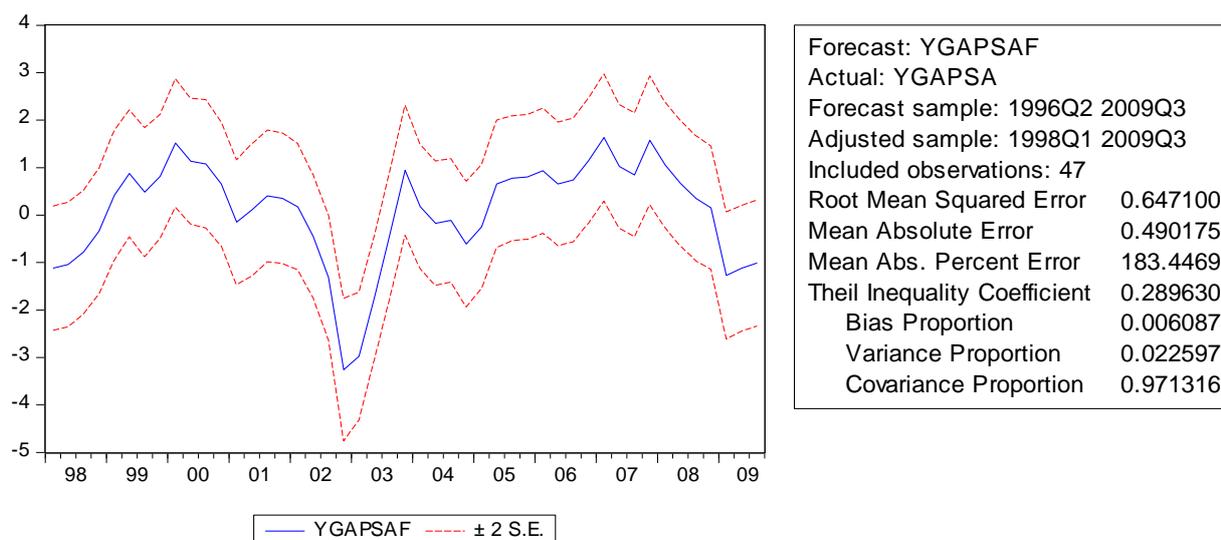In terms of forecasting, we need to provide the following information:

- **Forecast name**: In this edit box, we can give a series name to our forecast. EViews automatically suggests the name `ygapsaf` (with the suffix `f` standing for forecast), but you can

change it to any other name. Note, however, that the name you give to your forecast series should be different from the name of the dependent variable (or any other variable in your workfile), since the forecast procedure will overwrite data in an already existing series with the same name.

- **S.E. (optional)**: If desired, you may provide a name for the series to be filled with the forecast standard errors. If you do not provide a name, no forecast errors will be saved.

- **(Forecasting) Method**: There are two choices in EViews: **Dynamic forecast** and **Static forecast**. The **Dynamic forecast** option calculates dynamic, multi-step forecasts starting from the first period in the forecast sample. In dynamic forecasting, previously forecasted values for the lagged dependent variables are used in forming forecasts of the current value. This choice will only be available when the estimated equation contains dynamic components, e.g., lagged dependent variables or ARMA terms. As our equation contains `ygapsa(-1)`, the dynamic option is available to us. The **Static forecast** option calculates a sequence of one-step-ahead forecasts, using the actual − rather than forecasted − values for lagged dependent variables, if available.

- You may elect to always ignore coefficient uncertainty in computing forecast standard errors (when relevant) by leaving the **Coef uncertainty in S.E. calc** box unchecked.

- **Forecast sample range**: In terms of specifying the sample range to be used for the forecast, EView's default option is to set this sample to the workfile sample, which leads to an in-sample 'forecast'. By specifying a sample outside the sample used in estimation of the equation, we can instruct EViews to produce an out-of-sample forecast. Note that we need to provide values for any independent (or exogenous) variables in the out-of-sample forecasting period. For static forecasts, we must also supply the values for any lagged dependent variables.

- **Output**: We can choose to report the output of our forecast either as a graph or as a numerical forecast evaluation, or both. The option of forecast evaluation is only available if the forecast sample includes observations for which the dependent variable is observed.

- **Insert actual for out-of-sample observations**: By default, EViews will fill the forecast series with the values of the actual dependent variable for observations not in the forecast sample. This feature is convenient if you want to show the divergence of the forecast from the actual values. This is because, for observations prior to the beginning of the forecast sample, the two series will contain the same values. After the beginning of the forecast sample, they will diverge as the forecast differs from the actual. In some situations, however, you may want to have forecasted values only for the observations in the forecast sample. By unchecking this box, EViews will fill the out-of-sample observations with missing values.

Let us produce a **dynamic in-sample forecast** using our backward-looking augmented IS curve over the sample period from 1996 Q2 to 2009 Q3 (or `@all`). The forecasted values will be placed in the series `ygapsaf` and EViews will display a graph of the forecasts, the plus and minus two standard error bands of the forecast and several statistics useful for forecast evaluation (which will be discussed a little later on). This output for the dynamic forecast of `ygapsa` is given in Figure 4 below.

Figure 4: Dynamic in-sample forecast of `ygapsa`

Forecast: YGAPSAF	
Actual: YGAPSA	
Forecast sample: 1996Q2 2009Q3	
Adjusted sample: 1998Q1 2009Q3	
Included observations: 47	
Root Mean Squared Error	0.647100
Mean Absolute Error	0.490175
Mean Abs. Percent Error	183.4469
Theil Inequality Coefficient	0.289630
Bias Proportion	0.006087
Variance Proportion	0.022597
Covariance Proportion	0.971316

This is a 'dynamic' forecast for the – in-sample – adjusted period from 1998 Q1 to 2009 Q3. We lose three observations at the start of the sample as data on `rpr` are not available until 1997 Q2 and the backward-looking model includes `rpr(-3)` on the right-hand side. For every period, the previously forecasted value for `ygapsa(-1)` is used in forming the forecast of the subsequent value of `ygapsa`.[24] Dynamic forecasts are true multi-step forecasts (from the start of the forecast sample) since they use the recursively computed forecast of the lagged value of the dependent variable.

We can examine the actual versus the fitted values by creating a group containing `ygapsa` and `ygapsaf` and plotting the two series over the sample period from 1998 Q1 to 2009 Q3, as is done in Figure 5.

Figure 5 Actual versus dynamic forecast values of `ygapsa`

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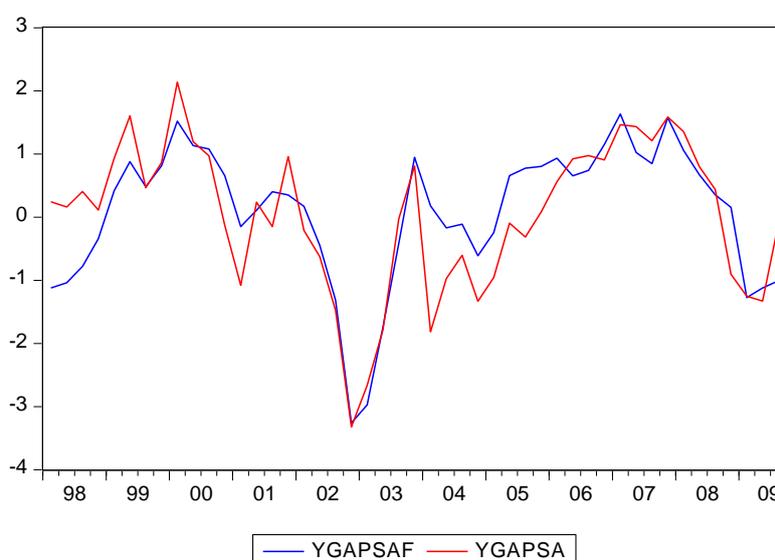
[24] The forecast values will be saved in the series `ygapsaf`, which has appeared in the workfile. Since `ygapsaf` is a standard EViews series, you may examine your forecasts using all of the standard tools for working with time-series objects.

The fit is not necessarily great: there are lengthy periods when the forecasted values lie either below or above the actual values.

Let us now produce a **static forecast** using our backward-looking augmented IS curve over the sample period from 1996 Q2 to 2009 Q3. To perform a series of one-step-ahead forecasts, click on **Forecast** on the equation toolbar and select **Static forecast**. The forecasted values should be given another name (I have called them `ygapsaf_static`) and EViews will display a graph of the forecasts, the plus and minus two standard error bands of the forecast and several statistics useful for forecast evaluation (which will be discussed a little later on). This output for the static forecast of `ygapsa` is given in Figure 6 below.
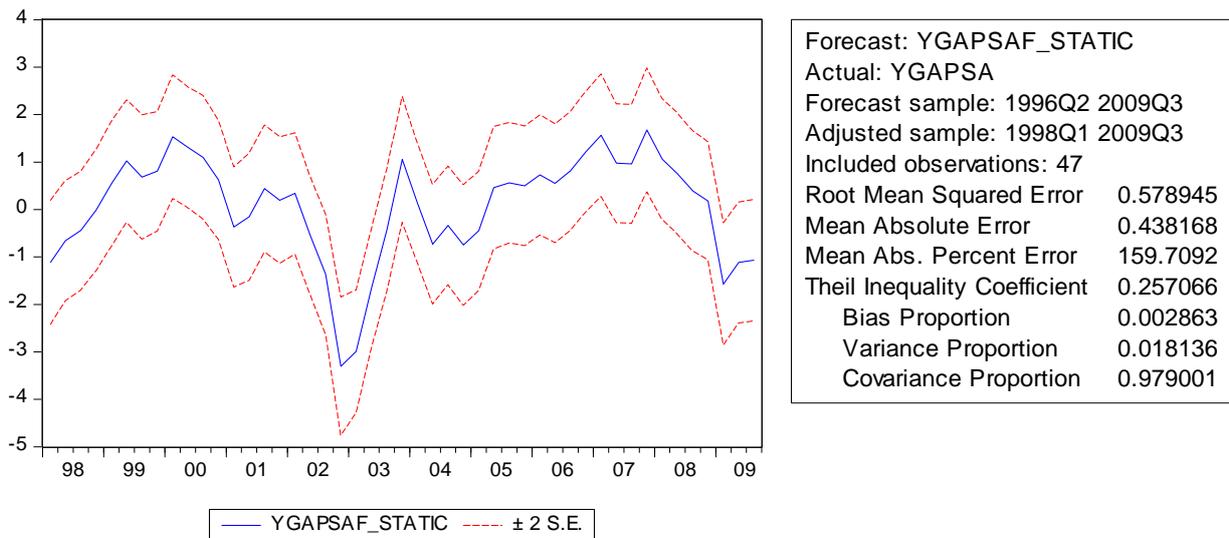
Figure 6: Static in-sample forecast of `ygapsa`

Forecast: YGAPSAF_STATIC	
Actual: YGAPSA	
Forecast sample: 1996Q2 2009Q3	
Adjusted sample: 1998Q1 2009Q3	
Included observations: 47	
Root Mean Squared Error	0.578945
Mean Absolute Error	0.438168
Mean Abs. Percent Error	159.7092
Theil Inequality Coefficient	0.257066
Bias Proportion	0.002863
Variance Proportion	0.018136
Covariance Proportion	0.979001

We can again compare the actual and fitted values from the static forecast by examining a line graph of a group containing `ygapsa` and `ygapsaf_static` (Figure 7).

Figure 7: Actual versus static forecast values of `ygapsa`
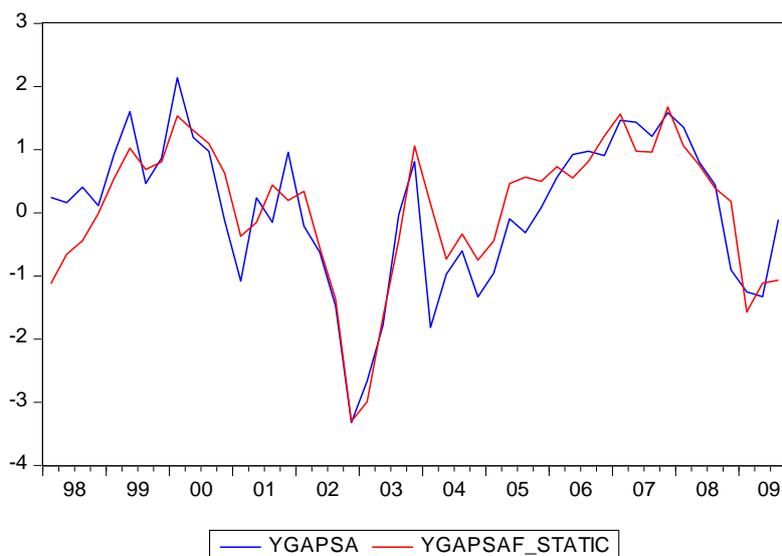
As can be seen from Figure 7, the one-step-ahead static forecasts are marginally more accurate than the dynamic forecasts since, for each period, the actual value of `ygapsa(-1)` is used in forming the forecast of `ygapsa`.[25] This is also borne out by the somewhat lower value of the root mean squared error for the static forecast (0.58) in comparison to the dynamic forecast (0.65). The root mean squared error values can be found in the respective boxes containing the forecast evaluation information.

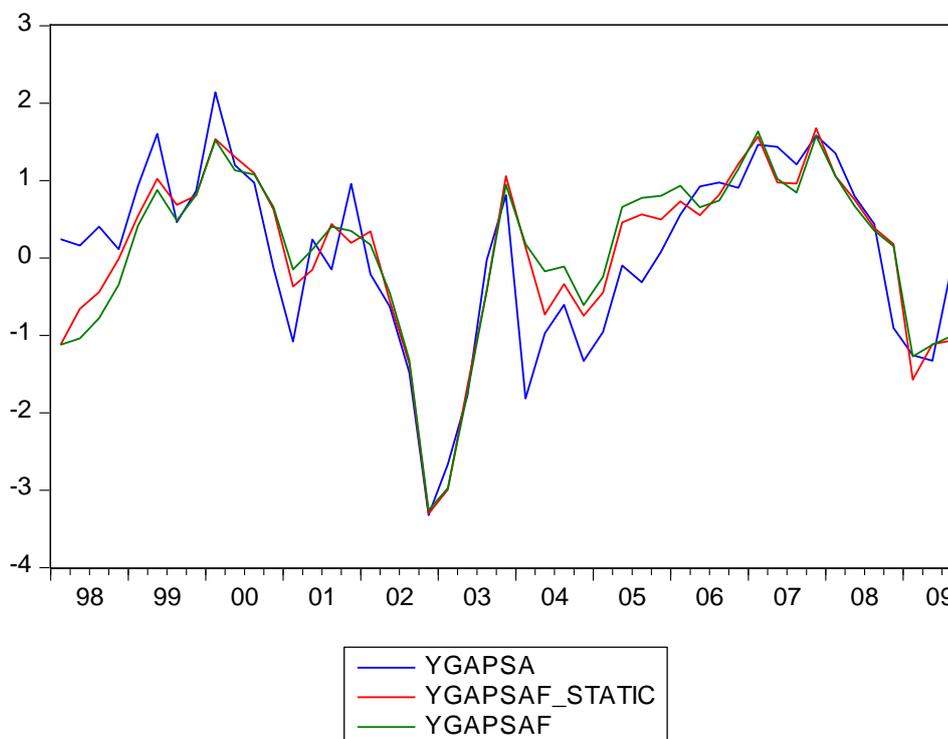**Figure 8: Forecasting performance**

Note, however, that static forecasting requires that data for both the exogenous and any lagged endogenous variables be observed for every observation in the forecast sample. We can collect the information on the (dynamic) forecast performance of the preferred equation specifications in Table 7, which replicates Table 2 in Patra and Kapur (2010, p. 28).

Table 7: Forecasting performance

Statistic	IS curve (Table 1, column 3)	Phillips curve (Table 3, column 3)	Monetary policy rule (Table 4, column 1)	Monetary policy rule (Table 4, column 2)
Mean error	-0.06	-0.07	0.40	0.23
Mean absolute error	0.49	1.08	1.05	0.88
Root mean squared error (RMSE)	0.65	1.39	1.32	1.07
RMSE (in per cent)				
Theil inequality measures	0.29	0.14	0.09	0.07
Bias	0.01	0.00	0.04	0.00
Variance	0.02	0.17	0.22	0.15
Covariance	0.97	0.83	0.74	0.85

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[25] These one-step-ahead static forecasts are the same forecasts used in the **Actual, Fitted, Residual Graph** displayed in Figure 3 above, which I have labelled `ygapsa_hat`.

Notes: The various statistics are for dynamic in-sample forecasts of individual equations. Bias, variance and covariance percentages may not sum to one due to rounding.

The root mean square error (RMSE) and the Theil inequality measure are helpful in evaluating the forecast. Theil's inequality measure is a form of forecast evaluation, as it always lies between zero and one. The closer the measure is to zero, the better the forecasting performance of the model, with zero indicating a perfect fit between the actual and the forecast values of the underlying series. In Table 7 above, all inequality coefficients are on the low side, indicating good fit.

Theil's inequality measure can be re-scaled and decomposed into three proportions of inequality: bias, variance and covariance, such that the three proportions add up to one. They are useful as a means of breaking down the forecast error into its characteristic sources.

The bias proportion is an indication of systematic error, since it measures the extent to which the **average** value of the forecast and the actual series deviate from each other. Whatever the value of Theil's inequality measure, we want the bias to be close to zero. The very small bias proportions of between zero and 4 per cent indicate that a small systematic bias in the form of over- or under-prediction is present. This means that the model is likely to be reliable for forecasting, and that there is no need to consider revising the model.

The variance proportion indicates the ability of the forecasts to replicate the degree of variability in the variable of interest. If the variance proportion is large then the actual series has fluctuated considerably whereas the forecast has not, or *vice versa*; this would indicate that the model should be revised.

Finally, the covariance proportion measures unsystematic error, i.e., it represents the remaining error after deviations from average values have been accounted for. Since it is unreasonable to expect predictions to be perfectly correlated with actual outcomes, this component of error is less worrisome than the other two. Ideally, this third measure should have the highest proportion of inequality.

For any value of the Theil inequality measure, an ideal distribution of inequality would correspond to bias and variance having values close to zero and covariance having a value close to one. Indeed, this is more or less what we find for the three preferred specifications of our model. The decomposition of the Theil inequality measure into bias, variance and covariance shows that bias and variance are generally quite low. Most of the Theil inequality measure can therefore be attributed to the covariance proportion, which measures the extent of unsystematic error.

6   Conclusions

In this exercise, we took the canonical three-equation NK model and augmented it with exogenous variables that seemed espcially pertinent in the Indian context. We estimated the ensuing model using GMM, which is the most appropriate estimation methodology for dealing with the potential endogeneity resulting from estimating forward-looking specifications.

The estimation results have revealed some stylised facts pertaining to the monetary transmission mechanism of the Indian economy. The application of the new Keynesian model to the Indian case provided several findings on the interaction between monetary policy and the structure and functioning of the economy. Using an augmented three-equation NK model, Patra and Kapur (2010) found that:

- aggregate demand reacts to interest rate changes with a lag of at least three quarters;
- institutional impediments in the Indian credit markets mean that monetary policy can have a persistent impact for up to two years;
- fluctuations in agricultural output can have both supply- and demand-side effects, which may warrant a monetary-policy response;
- inflation shows a lot of inertia and persistence when it sets in, irrespective of its source;

- external influences are increasingly important in light of the growing internationalisation of the Indian economy. At the moment, though, external demand factors such as the exchange rate or international interest rates are not that important: the exchange-rate pass-through to domestic inflation at the current time is still low;
- inflation turns out to be the dominant focus of monetary policy, accompanied by a strong commitment to the stabilisation of output (such that a Taylor-type rule characterises the monetary policy reaction function better than would be expected from a central bank with multiple objectives); and
- recent policy actions by the Reserve Bank of India (RBI) have raised the effective policy rate, but the estimated natural policy rate suggests some further tightening to normalise the policy stance.

While the NK model has provided many valuable theoretical insights, it is still quite difficult to take the canonical model to the data. The model as encapsulated in equations (3), (6) and (10) does not provide enough dynamics to match the observed volatility of real-world data. Calibrated NK or dynamic-stochastic general equilibrium (DSGE) model frequently try to match the data on average, but as highly-restricted reduced-form models, estimation frequently results in coefficients that fall outside the expected (theoretical) boundaries. Augmenting the NK model with exogenous variables as we have done in the present exercise provides a better match with the underlying data, but undermines the nice story-telling properties of the underlying NK model.

Nonetheless, the new Keynesian paradigm can be said to provide the intellectual rationale for the current monetary policy framework in India. As such, the findings of the paper support a forward-looking response of Indian monetary policy to expected inflation and the output gap.

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Appendix 1

`effective3`	Policy interest rate
`gdpr`	Real GDP (crore of rupees)[26]
`ygapsa`	Output gap, seasonally adjusted (s.a.)
`reert36`	36-currency real effective exchange rate (REER) index
`reer36gapsa`	36-currency REER gap, s.a.
`yagri`	Agricultural GDP (crore of rupees)
`ygapagrsa`	Agricultural GDP gap, s.a.
`wexpr`	World real exports (from IMF, nominal exports/unit value index)
`wexprgapsa`	World real exports gap, s.a.
`infwpi, infgdp, infcpi`	India's wholesale price, GDP deflator and consumer price inflation respectively (measured year-on-year)
`infwpidev, infgdpdev, infcpidev`	Deviation of actual inflation from the RBI's indicative inflation projection of 5 per cent = `infwpi - 5`, `infgdp - 5`, `infcpi - 5`
`infpc`	Primary article inflation (sub-group within wholesale price inflation, measured year-on-year)
`infglobal`	Global non-fuel commodity inflation (IMF index, measured year-on-year)
`exch`	Nominal exchange rate of Indian rupee against the US dollar
`dlexch4`	Annualised quarter-on-quarter variation in the log nominal exchange rate
`dlexcha`	Year-on-year variation in the log nominal exchange rate
`dlm3aadj, dlnfcaadj`	Year-on-year variation in the log of broad money and log bank credit
`fedtarget`	US federal funds target rate
`effective3gdp`	Real policy interest rate = policy interest rate minus year-on-year GDP deflator inflation (`effective3 – infgdp`)
`bses`	Bombay stock exchange index
`dlbsesa`	Year-on-year variation in log `bses`
`crr`	Cash reserve ratio

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[26] A crore is a unit in the Indian numbering system equal to ten million.

Appendix 2

As indicated in the exercise, the various specifications of the IS curve, the NKPC and the monetary policy reaction function were estimated over two sub-samples to assess the robustness of the estimation results. The first period is referred to as the pre-Lehman Brothers period and runs from 1997 Q2 to 2008 Q2, while the second period runs from 2002 Q2 to 2008 Q2. The latter period starts after significant changes were made to Indian monetary operations under the Liquidity Adjustment Facility (LAF).

IS curve

As already highlighted in the main text, there are very few differences between the coefficients obtained for the two sub-samples (Table A.1 and A.2) and the corresponding full-sample estimates in Table 3. The main difference is the insignificant output gap term in the augmented specifications in the second sub-sample from 2002 Q2 to 2008 Q2. In addition, the real interest rate enters significantly at the sixth, rather than the fifth, lag.

Table A.1: Estimates of the IS curve (first sample)

Variable	Alternative specifications					
	1	2	3	4	5	6
	Dependent variable: ygapsa					
	Sample period: 1997 Q2 – 2008 Q2					
constant	0.41	0.43	0.17	0.28	-0.05	0.07
	(4.00)	(4.23)	(1.96)	(2.54)	(-0.45)	(0.65)
rpr(-3)	-0.11			-0.12		
	(-3.03)			(-2.74)		
rpr(-6)		-0.16	-0.07		-0.02	-0.05
		(-4.94)	(-1.94)		(-0.40)	(-1.59)
ygapsa(-1)	0.55	0.37	0.37	0.29		0.26
	(8.27)	(5.72)	(6.15)	(3.56)		(3.51)
ygapsa(+1)			0.36		0.27	0.33
			(5.14)		(3.92)	(4.78)
ygapagrsa	0.16	0.26	0.14	0.22	0.24	0.16
	(3.64)	(5.54)	(3.69)	(4.83)	(6.62)	(3.34)
wexprgapsa				0.11	0.12	0.05
				(4.43)	(4.79)	(1.65)
reer36gapsa(-2)				-0.05	-0.04	-0.01
				(-2.16)	(-1.33)	(-0.505)
SEE	0.67	0.60	0.55	0.60	0.52	0.53
R-bar squared	0.68	0.77	0.81	0.75	0.83	0.82
Q-statistic	0.73	0.59	0.01	0.17	0.726	0.10
J-test	10.63	11.89	8.74	10.97	11.46	8.64
Significance level of *J*-test	0.64	0.54	0.73	0.45	0.41	0.57

Notes: See Table 1 in the main text.

Table A.2: Estimates of the IS curve (second sample)

Variable	Alternative specifications					
	1	2	3	4	5	6
	Dependent variable: ygapsa					
	Sample period: 2002 Q2 – 2008 Q2					
constant	0.22	0.28	0.33	-0.03	-0.16	-0.02
	(3.58)	(3.02)	(3.97)	(-0.20)	(-1.20)	(-0.09)
rpr(-5)	-0.08					

		(-2.88)					
rpr(-8)			-0.14	-0.14	-0.04	-0.01	-0.04
			(-2.71)	(-3.82)	(-0.71)	(-0.20)	(-0.66)
ygapsa(-1)		0.49		0.34	0.10		0.15
		(10.26)		(8.51)	(1.15)		(1.26)
ygapsa(+1)			0.28	0.16		0.00	0.04
			(3.92)	(2.17)		(-0.06)	(0.81)
ygapagrsa		0.23	0.27	0.19	0.22	0.24	0.21
		(8.48)	(12.42)	(7.79)	(7.49)	(8.05)	(5.46)
wexprgapsa					0.19	0.23	0.17
					(4.07)	(7.87)	(2.72)
reer36gapsa(-2)					-0.05	-0.07	-0.05
					(-2.35)	(-2.97)	(-1.96)
SEE		0.62	0.58	0.48	0.42	0.42	0.44
R-bar squared		0.80	0.82	0.88	0.90	0.90	0.90
Q-statistic		0.78	0.10	0.37	0.63	0.49	0.58
J-test		9.70	10.33	8.75	8.92	9.91	8.52
Significance level of *J*-test		0.72	0.67	0.72	0.63	0.54	0.58

Notes: See Table 1 in the main text.

New Keynesian Phillips curve

The main thrust of the results over the full sample period continue to hold for both the backward-looking as well as the hybrid NKPC in the two sub-samples (Table A.3). But we can spot some differences. To begin with, the null hypothesis that the coefficients on lagged and lead inflation sum to one can be rejected. In addition, the coefficient on the exchange rate is insignificant in the hybrid specification for the first sub-sample period (columns 2 and 4).

Table A.3: Estimates of the new Keynesian Phillips curve

Variable	Alternative specifications							
	1	2	3	4	5	6	7	8
	Dependent variable: infgdp							
	Sample period: 1997 Q2 – 2008 Q2				Sample period: 2002 Q2 – 2008 Q2			
constant	1.53	1.37	0.52	0.48	2.16	1.83	0.60	0.47
	(6.48)	(4.24)	(1.88)	(1.68)	(11.63)	(7.81)	(2.47)	(2.35)
ygapsa(-4)	0.25	0.17	0.17	0.13	0.31	0.27	0.12	0.12
	(3.57)	(1.86)	(3.02)	(1.85)	(7.50)	(3.84)	(2.52)	(2.39)
infgdp(-1)	0.58	0.60	0.49	0.49	0.45	0.54	0.44	0.48
	(10.57)	(8.96)	(10.67)	(8.47)	(12.16)	(10.29)	(11.88)	(9.81)
infgdp(+1)			0.36	0.36			0.42	0.42
			(7.85)	(6.67)			(10.06)	(15.45)
infglobal	0.04	0.05	0.01	0.01	0.05	0.05	0.00	0.00
	(4.67)	(3.31)	(1.66)	(0.98)	(4.83)	(5.83)	(0.28)	(0.10)
dum1998q3q4	3.80	3.52	1.66	1.36				
	(5.58)	(3.87)	(2.30)	(1.53)				
dlexcha		0.03		0.01		0.04		0.03
		(1.00)		(0.49)		(1.63)		(1.66)
SEE	0.96	0.94	0.78	0.80	0.90	0.90	0.76	0.75
R-bar squared	0.67	0.68	0.78	0.77	0.44	0.45	0.61	0.62
Q-statistic	0.54	0.47	0.00	0.00	0.84	0.88	0.27	0.15
J-test	11.92	12.19	12.55	12.75	11.96	10.41	9.82	9.54
Significance level of *J*-test	0.75	0.66	0.64	0.55	0.80	0.84	0.88	0.85
Chi-squared(1)			5.55	4.96			7.08	7.17
Significance			0.02	0.03			0.01	0.01

Monetary policy reaction function or Taylor rule

We evaluate two different variants of the monetary policy reaction function. As mentioned in the text, we start by estimating a Taylor rule in which we replace the output gap variable (`ygapsa`) by its **first difference** (`dygapsa`). This is done as a robustness check against potential measurement errors in the **level** of the output gap, which is an unobserved variable.

Using the GDP deflator as our measure of inflation, the results are broadly in line with those in Table 6, which uses the level of the output gap. Starting with the baseline specification (Table A.4, column 1), one-quarter ahead inflation is significant throughout, while the (lagged) first difference of the output gap is not (*p*-value: 0.07). The Taylor principle holds in only one of the four specifications. The long-run coefficient on the first difference of the output gap also does not exceed unity. Note that the exchange-rate variable in column 2 is wrongly signed, but significant. Augmenting the specification with the US federal funds target rate (either contemporaneously or lagged one quarter) still results in insignificant coefficients on the first difference of the output gap. At the same time, `fedtarget` as well as `fedtarget(-1)` are both significant.

Table A.4: Estimates of the monetary policy reaction function
(using the first difference of the output gap)

Variables	Alternative specifications			
	1	2	3	4
	Dependent variable: `effective3`			
	Sample period: 1997 Q2 – 2009 Q3			
constant	0.78	0.53	1.35	1.74
	(1.81)	(1.27)	(3.38)	(4.07)
infgdpdev(+1)	0.14	0.13	0.24	0.24
	(1.96)	(2.22)	(4.17)	(4.09)
dygapsa(-1)	0.12	0.11	0.02	0.03
	(1.60)	(1.43)	(0.41)	(0.57)
effective3(-1)	0.87	0.91	0.69	0.59
	(13.30)	(15.57)	(9.36)	(7.27)
dlexch4(-1)		-0.01		0.00
		(-1.67)		(-0.19)
fedtarget			0.22	
			(4.55)	
fedtarget(-1)				0.27
				(4.87)
SEE	0.66	0.64	0.56	0.55
R-bar squared	0.82	0.84	0.87	0.88
Q-statistic	0.37	0.53	0.79	0.78
J-test	10.04	9.49	7.67	6.19
Significance level of *J*-test	0.26	0.22	0.36	0.40
Long-run coefficient on inflation	1.07	1.47	0.76	0.59
Long-run coefficient on output gap	0.92	1.20		
Natural policy rate	6.14	5.81		

Notes: Estimation is by the generalised method of moments (GMM) over the sample period 1997 Q2 to 2009 Q3 using quarterly data and one lag each of the following instruments: `effective3`, `dygapsa`, `dwexprgapsa`, `infgdpdev`, `incpidev`, `infwpidev`, `infglobal`, `dlexch4`, `dlm3`, `dlnfc` and `fedtarget`. Variables are defined as follows: `dygapsa` is the first difference of the output gap = real seasonally-adjusted GDP less its Hodrick-Prescott filtered series;

`dwexprgapsa` = first difference of world real export gap = seasonally-adjusted world real exports less its Hodrick-Prescott filtered series. Other variables and notes are as in Table 3 in the main text.

In terms of the robustness analysis, we find that results for the forward-looking model in the second sub-sample (2002 Q2 to 2008 Q2) are qualitatively similar to the full sample (Table A.5). In all but one specification (column 6) is the long-run coefficient on inflation below unity. Looking at the pre-Lehman Brothers sample, the main difference with the full sample results is that the long-run coefficient on inflation falls below unity, even in the baseline specification of column 1.

Table A.5: Estimates of the forward-looking monetary policy reaction function

Variable	Alternative specifications							
	1	2	3	4	5	6	7	8
	Dependent variable: `effective3`							
	Sample period: 1997 Q2 – 2008 Q2				Sample period: 2002 Q2 – 2008 Q2			
`constant`	0.86	0.92	0.83	1.14	0.37	0.27	0.45	0.60
	(3.18)	(2.90)	(3.06)	(3.56)	(2.19)	(1.89)	(4.19)	(3.32)
`infgdpdev(+2)`	0.08	0.10	0.10	0.10	0.04	0.04	0.06	0.04
	(1.93)	(1.82)	(1.99)	(1.77)	(1.41)	(1.56)	(4.08)	(2.26)
`ygapsa(+2)`	0.17	0.19	0.06	0.03	0.14	0.15	0.04	0.09
	(2.47)	(2.43)	(0.74)	(0.46)	(4.73)	(6.19)	(1.50)	(2.40)
`effective3(-1)`	0.87	0.86	0.82	0.73	0.95	0.97	0.86	0.85
	(22.06)	(19.04)	(15.43)	(10.41)	(30.06)	(37.96)	(39.27)	(16.67)
`dlexch4(-1)`		0.00		0.00		0.01		0.01
		(0.54)		(0.75)		(2.27)		(1.82)
`fedtarget`			0.10				0.13	
			(1.67)				(4.94)	
`fedtarget(-1)`				0.18				0.12
				(2.51)				(2.31)
SEE	0.47	0.48	0.45	0.44	0.30	0.27	0.27	0.25
R-bar squared	0.90	0.89	0.91	0.91	0.95	0.95	0.96	0.96
Q-statistic	0.72	0.72	0.40	0.40	0.60	0.87	0.38	0.49
J-test	7.58	7.89	8.17	7.96	5.73	6.62	6.25	7.66
Significance level of *J*-test	0.48	0.34	0.32	0.24	0.68	0.47	0.51	0.26
Long-run coefficient on inflation	0.61	0.69	0.55	0.39	0.77	1.58	0.46	0.30
Long-run coefficient on output gap	1.27	1.29			2.77	5.89		0.58
Long-run coefficient on exchange rate		0.02		0.02		0.45		0.07

Notes: See Table 6 in the main text.

Table A.6 shows the sub-sample estimates for the contemporaneous specification of the monetary policy reaction function and assesses the robustness of the full-sample estimation results in Table 4 in the main text. We find that the results are largely similar to the full-sample specification: the coefficient on inflation is significant in some specifications, especially in the second sub-sample, with a long-run coefficient below unity. Patra and Kapur (2010) ascribe this fact to discrete fiscal and supply-side policy interventions, which affect the Indian monetary policy reaction function. Given the large weight of food articles in the consumption basket, recurrent supply shocks result in a volatile inflation process in India. Other interventions occur to soften the impact of international oil and commodity price fluctuations on the Indian public. As such, import duties are frequently reduced to make imports less costly and domestic prices administered to mitigate the pass-through of price fluctuations.

Table A.6: Estimates of the contemporaneous monetary policy reaction function

Variable	Alternative specifications							
	1	2	3	4	5	6	7	8
	Dependent variable: `effective3`							
	Sample period: 1997 Q2 – 2008 Q2				Sample period: 2002 Q2 – 2008 Q2			
`constant`	1.02	1.07	1.07	1.15	0.80	0.73	0.36	0.64
	(4.89)	(3.89)	(4.13)	(4.39)	(3.85)	(2.74)	(2.20)	(3.70)
`infgdpdev`	0.06	0.07	0.06	0.07	0.08	0.09	0.09	0.09
	(1.58)	(1.95)	(1.34)	(1.66)	(3.68)	(2.23)	(3.06)	(3.61)
`ygapsa`	0.20	0.23	0.17	0.15	0.15	0.18	0.04	0.04
	(3.69)	(3.29)	(2.89)	(2.13)	(3.13)	(3.90)	(1.27)	(1.00)
`effective3(-1)`	0.84	0.83	0.80	0.76	0.88	0.90	0.90	0.83
	(26.16)	(19.59)	(17.00)	(13.60)	(24.35)	(20.25)	(30.37)	(24.90)
`dlexch4(-1)`		0.01		0.01		0.01		0.01
		(0.99)		(1.13)		(1.52)		(1.65)
`fedtarget`			0.07				0.11	
			(1.31)				(3.96)	
`fedtarget(-1)`				0.12				0.16
				(1.89)				(5.18)
SEE	0.54	0.54	0.53	0.51	0.31	0.30	0.27	0.24
R-bar squared	0.89	0.89	0.90	0.91	0.94	0.95	0.96	0.97
Q-statistic	0.15	0.20	0.09	0.10	1.00	0.90	0.59	0.42
J-test	5.18	6.03	6.80	7.00	6.71	7.96	3.52	4.50
Significance level of *J*-test	0.74	0.54	0.45	0.32	0.57	0.34	0.83	0.61
Long-run coefficient on inflation		0.44		0.31	0.69	0.88	0.86	0.56
Long-run coefficient on output gap	1.23	1.36	0.85	0.62	1.32	1.88		
Long-run coefficient on exchange rate				0.03		0.08		0.04

Notes: See Table 4 in the main text.