Estimating the New Keynesian Phillips Curve (NKPC) with Fat-tailed Events

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Abstract

This paper provides estimation of the New Keynesian Phillips curve accounting for the unexpected large shocks such as Covid-19. The recent pandemic distorted the estimates of the output gap derived using the regular trend cycle decomposition of GDP (HP Filter, BP Filter, Kalman Filter). We propose a modified unobserved components model (UCM) by introducing an additional Student-t distributed irregular component in the trend cycle decomposition of GDP, which successfully isolates transitory shocks like COVID-19 from trend and cycle estimates. We also construct a model-based measure of inflation expectations that captures adaptive learning from a long inflation history and real-time updating during the pandemic. For India, we find a stable linear NKPC. Our results demonstrate that accounting for fat-tailed events is crucial for obtaining reliable Phillips curve estimates in emerging markets.

JEL Classification: C5, C6, E3

Key Words: Philips Curve, Potential Growth, Output Gap, Inflation Expectations, Unobserved Components Model, Kalman Filter, Almon Lag.

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1. Introduction

The New Keynesian Phillips Curve (NKPC) is a cornerstone of monetary policy because it links current inflation to expected future inflation and the economic slack (output gap), offering a forward-looking framework for price dynamics. Empirically, however, estimating the NKPC is difficult due to structural breaks, state dependence, nonlinearities, etc. in the inflation–output gap relationship. These challenges are especially pronounced in emerging markets undergoing rapid structural change, which are further exacerbated by fat-tailed shocks such as COVID-19 generate extreme outliers and distort traditional estimates

This study attempts to address these issues with three objectives: (i) to develop fat-tail-robust estimates of the output gap and inflation expectations for large emerging market like India, (ii) to test whether these robust measures yield a stable closed-economy NKPC using regressions, and (iii) to jointly estimate the output gap and NKPC parameters, evaluating both their consistency with earlier results and the ability of the joint estimation to improve estimation accuracy.

Starting with estimation of output gap, a central requirement for its estimation is an accurate measure of potential output, as output gap is defined as the deviation of output from the potential output. The potential output is the maximum level of goods and services an economy can produce sustainably, when all resources are used efficiently without creating inflationary pressures. Since potential output is unobservable, it is usually estimated using production functions, Okun's Law, or statistical filters such as the Hodrick–Prescott (HP), Band-Pass (BP), or Kalman filter. In India and other emerging markets, limited labor market data restricts the use of structural approaches, leaving statistical filters as the dominant method. However, large shocks like COVID-19 severely distort these filters, leading to implausible estimates of the trend and cycle. To address this, we extend the unobserved components model (UCM) by adding an irregular component: a Student-t distributed measurement error with time-varying volatility. This component is incorporated into the measurement equation alongside the trend (potential output) and cycle (output gap), and the model is estimated within a Bayesian Kalman filter framework. This fat-tailed robust UCM framework, isolates rare shocks such as COVID-

19, preventing them from contaminating estimates of trend (potential output) and cycle (output gap).

We also construct a fat-tail-robust measure of inflation expectations. Theory and evidence suggest that expectations depend on a longer history of inflation, and that during extreme shocks, households update beliefs in real time rather than relying only on past inflation. To capture this, we regress household three-month-ahead inflation expectations on 16 lags of core inflation[3] using a second-degree Polynomial Almon Distributed Lag model, augmented with a COVID dummy from the Oxford Stringency Index[4]. This specification captures both adaptive learning from long inflation histories and contemporaneous updating during fat-tailed shocks. Using the Almon lag polynomial instead of OLS allowed us to capture the effect of a long history of past inflation on household expectations in a more parsimonious way, reducing both multicollinearity among lagged core inflation terms and the loss of degrees of freedom. The predicted values from the model are used as the measure of inflation expectations. To correct for the persistent upward bias in household surveys, we subtract the constant term from predicted values, yielding an expectations series that closely tracks a 16-quarter moving average of core inflation, except during COVID when expectations shifted sharply upward.

Finally, we estimate the NKPC using two approaches: (i) a regression model with output gap from the univariate UCM and derived inflation expectations as the explanatory variables and core inflation[5] as the dependent variable, and (ii) a multivariate Kalman filter which extends the univariate Kalman filter by adding another measurement equation to model core inflation as a function of the derived inflation expectations and the output gap.

Both approaches confirm a stable linear NKPC for India, with the output gap coefficient positive and significant. Moreover, the multivariate UCM delivers parameter estimates consistent with earlier results, but with substantially more robust measures of the output gap and potential growth than those obtained from the univariate framework. Also, it addresses one of the major criticisms of using univariate filter is that there is no link to inflation in the

[3] (Goyal and Parab, 2021) show that while food inflation has a significant short-run impact on Indian households' inflation expectations, in the long run it is demand-driven core inflation that dominates. Since our model focuses on the long-horizon relationship between inflation and household expectations, we use lags of core inflation rather than headline inflation.

[4] Oxford Stringency Index is a global panel database of pandemic restriction. The Covid Dummy is defined as 1 when the Oxford stringency index is greater than 0. (Hale et al., 2021)

[5] We have focused CPI core inflation in our study, as it is derived by removing food and fuel inflation (which are volatile components driven primarily by supply shocks) to focus on demand side movement of inflation (explained by NKPC)

estimation of potential output which is central to the definition of potential output which adds more credibility to our modified UCM approach.

The rest of the paper is organized as follows. Section 2 presents the literature survey and key contributions of the study. Section 3 discusses the methodology, Section 4 presents the empirical findings, and Section 5 concludes.

2. Literature Survey

The NKPC fundamentally links economic slack (the output gap) to inflation, while controlling for inflation expectations. A large body of literature has examined this relationship, highlighting several challenges in estimation, including structural breaks, state dependence, and non-linearities in the output gap–inflation link (Cristini and Ferri, 2021). These challenges are even more pronounced in emerging markets, where rapid structural transformations, evolving labor markets (Behera et al., 2025), and frequent macroeconomic shocks complicate the estimation. The COVID-19 pandemic further amplified these difficulties by introducing fat-tailed shocks, which distort both output gap and inflation expectation measures.

To address such challenges, the literature has proposed non-linear econometric approaches such as regime-switching, threshold, state-dependent models, time varying parameters models, etc (Ball and Mazumder, 2019; Hazell et al., 2022; Doser et al., 2023). They gave evidence of non-linear convex NKPC, where it is flat when, inflation pressures are low but steepens when inflation pressures increase (Harding, et al., 2024). While (Gudmundsson et al., 2024) have showed that Philips curve across advance economies have steepened in the post-COVID period. More recently, researchers have also applied Explainable Machine Learning (ExpML) methods to capture structural breaks and non-linear dynamics, showing substantial gains in inflation forecasting within the NKPC framework (Pratap et al., 2025). However, this consensus on non-linearity is not universal, (Doser et al., 2023) demonstrate that the linear specification of the NKPC cannot be rejected once consumer inflation expectations are properly accounted for.

Building on these insights, our contribution is to estimate the NKPC under fat-tailed events by first developing robust measures of the output gap and inflation expectations applicable to emerging markets (detailed in the section later). We then embed these measures into a simple linear NKPC framework, with core inflation[6] as the dependent variable and the derived output gap and expectations as explanatory variables and check if derived measures of output gap and inflation expectations lead to a stable linear close economy NKPC.

Beginning with the estimation of the output gap, the literature offers multiple methods for estimating both the output gap and potential output. First is the production function approach, in which the potential output is estimated based on factors of productions such as capital stock, labour force and total factor productivity and then the output gap is estimated by calculating the deviation of output from the potential output (Chalaux, T., & Guillemette, Y., 2019). The second approach estimate output gap based on Okun law, which links the deviation of the unemployment rate from the Non-Accelerating Inflation Rate of Unemployment (NAIRU) to the output gap (Lancaster, D., & Tulip, P., 2015). However, for many emerging markets like India, these methods are challenging due to unavailability for long time series labour force or employment data.

As an alternative, statistical filters such as the HP filter, BP filter, and Hamilton filter have been widely applied in emerging markets to estimate the trend and output gap (Anand et al., 2014). Another statistical method is the Beveridge–Nelson decomposition of GDP after estimating ARIMA model of the GDP. While each of these techniques has their own technical advantages and disadvantages, they share key limitations: they rely solely on statistical filtering, exclude relevant economic variables from the trend–cycle decomposition. Moreover, their performance deteriorates in the post-COVID period because the large outliers in GDP during the pandemic distort the estimates. In addition, potential output estimates derived from purely statistical techniques typically lack confidence intervals, making it difficult to assess their reliability.

In this regard, the Unobserved components models (UCM) can come handy. The UCM estimates the trend and cycle as the unobserved latent variables which are estimated using Kalman filter (Kuttner, 1994). The trend is estimated as random walk with drift or random walk with stochastic slope. The cycle (output gap) is modelled as a stationary AR1 or AR2 process. Thus, it is extremely useful in estimation of output gap in the emerging markets, which lack long employment or labour series as it only requires GDP series for the univariate version. In addition, UCM allows to construct confidence/credible intervals around the estimates, enabling

[6] We have focused CPI core inflation in our study, as it is derived by removing food and fuel inflation (which are volatile components driven primarily by supply shocks) to focus on demand side movement of inflation (explained by NKPC)

us to assess the reliability of the estimates. The UCM can be extended to multivariate UCM models, where other macroeconomic variables such as inflation can be modelled simultaneously based on macroeconomic framework e.g. NKPC. The multivariate UCM improves the estimates of univariate UCM by making them more economically interpretable, by including the economic relationship between the output gap and inflation in the estimation (Kuttner, 1994 and Grant, & Chan, 2017).

There are two distinct strands in the UCM model-based output gap estimation, in the one strand there is no correlation between the trend and cycle innovation (Kuttner, 1994), and in the other strand the trend and cycle innovation are modelled to be contemporaneously correlated (Morley et al. 2003 and González-Astudillo & Roberts, 2022). In the UCM with no correlation between the trend and cycle innovation, the shocks to cycle and trend are orthogonal, i.e. variations in output gap is independent of shocks in potential output. In this case the estimated cycle exhibits large persistence and trend is slow moving. On other hand in the UCM model with correlated trend cycle innovations, assumes that common shocks affects both trend and cycle, it is useful when hysteresis effect exists, i.e., shocks not only affect the cycle but also trend through hysteresis. The cycles estimated using the second strand leads to less persistence cycle and more volatile trend like trend cycle decomposition results from the Beverage-Nelson Decomposition (Morley et al., 2003).

In the post-COVID period, the presence of extreme outliers in the GDP series makes traditional UCM models unreliable for trend–cycle decomposition. As shown in Appendix Figure A1, traditional univariate UCM models like (Kuttner, 1994) where in the measurement equation, the output is decomposed only in trend and cycle, generate cycles with extreme fluctuations during the COVID period, and estimates for other periods are also distorted by these outliers. Potential growth estimates fall close to zero during the lockdown. This occurs because the COVID-19 shock was not a regular cyclical event: the sharp contraction during lockdown and the subsequent rebound after restrictions were lifted, distort estimates of cycle persistence and trend reversion speed. Also, the abrupt output drop pulls down the estimated trend excessively, leading to implausible long-run potential output estimates.

To address the outliers in post-COVID data, we propose a modified UCM model that decomposes log GDP into four components: trend, trend growth, cycle, and irregular component (shock). Unlike the traditional UCM framework (Kuttner, 1994), which only separates trend, trend growth, and cycle, our approach adds an irregular component to capture extreme, non-repetitive events such as pandemics, natural disasters, or sudden policy shocks. We model this irregular component within the UCM decomposition using a Bayesian Kalman Filter, specifying it as Student-t distributed measurement error with time-varying volatility, characterized by low baseline volatility that spikes during irregular events such as COVID lockdowns. Then, we have also extended our modified univariate UCM to multivariate (bivariate) UCM. This framework jointly estimates the output gap and the inflation dynamics, making the estimate of the potential output aligned with the definition of the potential output. The detailed estimation strategy for this modified UCM approaches is presented in the following section.

This framework adds to the literature of estimating output gap and trend growth (potential output growth) of GDP with the post-COVID assessment (Morley et al., 2022 and Granados & Parra-Amado, 2024). In this regard, literature have largely focused on Beverage Nelson Trend-cycle Decomposition based on large Bayesian VAR(BVAR), with BVAR modification is done on the lines of (Lenza and Premiceri, 2022) in which outlier adjustment is done in the measurement errors for specific outlier quarters in the VAR estimation. Similarly, (Patra et al., 2021, Pattanaik et al., 2022 and Behera, 2024) have used a multi-variate UCM approach, in which they have disaggregated log of GDP into trend, cycle and shocks instead of conventional approach of disaggregating log GDP into trend and cycle to capture the shocks during COVID. The shocks are proxied through Oxford Stringency Index, which denotes the stringency of lockdown measures in a country. By contrast, our modified UCM approach incorporates shocks directly into the trend–cycle decomposition as an additional component, avoiding the need for ad hoc identification of outlier quarters or reliance on external proxies like the Stringency Index.

Coming to inflation expectations, reliable long-series measures of household inflation expectations are still limited. Survey-based expectations often exhibit bias, abrupt fluctuations, and discontinuities in historical coverage (Ruhi et al., 2025). Common proxies, such as using a few lags of core inflation (typically one to four; Kuttner, 1994), fail to adequately capture the adaptive nature of expectation formation. Empirical evidence indicates that agents rely on longer histories of past inflation when forming expectations (Chari and Mishra, 2016). Moreover, relying solely on past inflation overlooks real-time adjustments in expectations triggered by economic shocks and disruptions.

However, despite their limitations listed above, survey-based measures of inflation expectations remain informative. Coibion et al. (2018) show that incorporating them into NKPC estimation helps address key challenges in identifying the Phillips curve. Supporting this view, (Dietrich et al., 2022) find that U.S. households reported higher inflation expectations during COVID, reflecting heightened uncertainty, even though the economy was below potential, contrasting with professional forecasters in the SPF, who expected lower inflation due to demand slack. Hence, while survey-based household expectations require adjustment to mitigate their shortcomings, they provide valuable information for NKPC estimation. To address the limitations of existing survey measures and proxies for inflation expectations, we construct a model-based proxy using data on households' three-month-ahead inflation expectations which is explained in the next section.

3. Methodology

The empirical framework of this study is grounded in the New Keynesian Phillips Curve (NKPC), which establishes a forward-looking relationship between inflation, expectations, and real economic activity (Coibion et al., 2018). The NKPC is specified as:

$$\pi_t = \beta * E_t(\pi_{t+1}) + \kappa * x_t \qquad (1)$$

where π_t denotes core inflation at time t, $E_t(\pi_{t+1})$ represents the expected value of next period's core inflation, and x_t is the output gap serving as a proxy for real economic slack. The parameter β captures the discount factor and reflects the degree to which economic agents form forward-looking expectations, while κ denotes the slope of the curve, indicating the sensitivity of inflation to fluctuations in the output gap. This specification highlights the central role of expectations in the inflation process and provides a tractable framework for empirically testing the responsiveness of inflation to real economic activity in line with modern macroeconomic models.

We estimate the NKPC model using two approaches[7]. First method is simple linear regression approach on the equation (1), where the output gap is estimated using the univariate Kalman filter and inflation expectation is estimated using the lags of core inflation and Covid dummy explain later in this section. The second approach is the Bayesian bivariate UCM, where the

[7] Data Sources- GDP and CPI – National Statistical Organisation & Household Inflation Expectations - Reserve Bank of India

output gap and the inflation dynamics are simultaneously estimated. The methodology is defined later in this section.

3.1 Estimate of Inflation Expectation

To address the limitations associated with different measures and proxies for inflation expectation, we construct a model-based proxy for household inflation expectations using the available data of 3 months ahead inflation expectations of the households. Specifically, household survey 3 months ahead inflation expectations are regressed on sixteen lags of core inflation[8] (to model long horizon relationship between household inflation expectations and lags of core inflation) along with a COVID-19 dummy, derived from the Oxford Stringency Index (Hale et al., 2021), to capture pandemic-induced disruptions:

$$\pi_t^e = \alpha + \sum_{i=1}^{16} \beta_i \, \pi_{t-i} + \gamma \, D_t^{COVID} + \varepsilon_t \qquad (2)$$

where π_t^e denotes household inflation expectations at time t, π_{t-i} represents the i^{th} lag of core inflation, D_t^{COVID} is the COVID dummy variable defined as $D_t^{COVID} = 1_{\{Oxford\ Stringency\ Index > 0\}}$, and ε_t is the error term. The constant term defines the time-invariant persistent gap between household inflation expectation and lags of core inflation. Furthermore, the coefficient of the COVID dummy highlights that agents updated their expectations contemporaneously in response to the pandemic shock.

Instead of OLS estimation of the model in Equation 2, we are using Almon Polynomial Distributed Model of degree 2[9] (Almon, 1965) due to high multicollinearity between the lags of core inflation and higher degrees of freedom required to estimate 16 coefficients. The Almon lag technique imposes the restriction that the coefficients β_i on the 16 lags lie on a polynomial of degree 2. This means instead of estimating 16 different β_i coefficients, we estimate three parameters that define a quadratic function as in Equation 3.

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[8] (Goyal and Parab, 2021) show that while food inflation has a significant short-run impact on Indian households' inflation expectations, in the long run it is demand-driven core inflation that dominates. Since our model focuses on the long-horizon relationship between inflation and household expectations, we use lags of core inflation rather than headline inflation.

[9] The number of lags and degrees of the Almon polynomial is decided based on maximizing adjusted R-square of the model. (See Figure A4 of appendix)

$$\beta_i = \delta_0 + \delta_1 * i + \delta_2 * i^2 \ldots\ldots\ldots\ldots\ldots. (3)$$

After replacing β_i in Equation 2 using Equation 3, we get Equation 4

$$\pi_t^e = \alpha + \sum_{i=1}^{16}(\delta_0 + \delta_1 * i + \delta_2 * i^2) * \pi_{t-i} + \gamma D_t^{COVID} + \varepsilon_t \ldots\ldots\ldots\ldots\ldots\ldots (4)$$

Then, we have arranged the left side of the Equation 4 by parameters of the quadratic function in the Equation 3 to get Equation 5. Now, we need to just estimate 3 parameters of the Almon polynomial instead of 16 parameters in case of simple OLS, thus leading to a more parsimonious modelling of relationship between lags of core inflation and household inflation expectations.

$$\pi_t^e = \alpha + \delta_0 * \sum_{i=1}^{16} \pi_{t-i} + \delta_1 * \sum_{i=1}^{16} i * \pi_{t-i} + \delta_2 * \sum_{i=1}^{16} i^2 * \pi_{t-i} + \gamma D_t^{COVID} + \varepsilon_t \ldots\ldots\ldots\ldots (5)$$

The fitted values from the regression, after accounting for the constant term, is the proxy for forward-looking inflation expectations. This adjusted measure is compared with the 16 quarters moving average of the core inflation, another proxy for the inflation expectation. By construction, this measure provides a more realistic representation of expectation formation, incorporating both adaptive learning and real-time responses to extraordinary shocks.

3.2 Univariate Kalman filter with fat tail

A Bayesian state-space framework is employed to decompose real GDP into its long-run trend, cyclical fluctuations, and fat-tailed disturbances. The observed log GDP, y_t is modeled as the sum of the trend component μ_t, the cyclical component c_t, and a disturbance term ε_t. Formally, the measurement equation is specified as:

$$y_t = \mu_t + c_t + \varepsilon_t, \quad \varepsilon_t \sim t_\nu\left(0, \frac{\sigma_{e,t}^2}{\lambda_t}\right) \qquad (5)$$

$$x_t = [\mu_t, \beta_t, c_t, c_{t-1}]' \qquad (6)$$

$$x_t = F * x_{t-1} + \omega_t, \quad \omega_t \sim N(0, Q) \qquad (7)$$

where ν denotes the degrees of freedom and λ_t is a latent Gamma-distributed scaling factor, which induces the heavy-tailed error distribution. This hierarchical formulation ensures robustness to extreme economic shocks while maintaining conditional Gaussianity for estimation. β_t represents the slope of the trend, or the time-varying potential growth rate. The transition matrix F and the innovation covariance matrix Q for the state dynamics are:

$$F = \begin{bmatrix} 1 & 1 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & \varphi_1 & \varphi_2 \\ 0 & 0 & 1 & 0 \end{bmatrix}$$

$$Q = \begin{bmatrix} \sigma_v^2 & 0 & 0 & 0 \\ 0 & \sigma_s^2 & 0 & 0 \\ 0 & 0 & \sigma_c^2 & 0 \\ 0 & 0 & 0 & 0 \end{bmatrix}$$

The state innovation covariance matrix Q is a diagonal matrix indicating that there is no correlation between the innovations of trend and cycle. σ_v^2 is the variance of trend innovation, σ_s^2 is the variance of slope innovation and σ_c^2 is the cycle innovation. As discussed earlier, the trend is μ_t is modelled as a random walk with stochastic slope. The cyclical component follows an autoregressive process of order two, with AR1 parameter as φ_1 and AR2 parameter as φ_2, which allows for persistence and oscillatory business cycle dynamics.

Conditional on the scaling factors $\Lambda = \{\lambda_t\}$, the model admits a Gaussian distribution. The conditional density of the observed series is:

$$p(y_t \mid x_t, \theta, \lambda_t) = \boldsymbol{N}\left(y_t \,\middle|\, \mu_t + c_t, \frac{\sigma_{e,t}^2}{\lambda_t}\right), \tag{8}$$

so that the joint likelihood is:

$$L(\theta \mid Y, X, \Lambda) = \prod_{t=1}^{T} \boldsymbol{N}\left(y_t \,\middle|\, \mu_t + c_t, \frac{\sigma_{e,t}^2}{\lambda_t}\right), \tag{9}$$

where $\theta = \{\phi_1, \phi_2, \sigma_v^2, \sigma_s^2, \sigma_c^2, \nu\}$. Integration over latent states is infeasible in closed form, motivating simulation-based inference.

We adopt weakly informative but proper priors. The AR coefficients ϕ_1, ϕ_2 follow normal distributions subject to stationarity restrictions, while the variance components $\sigma_v^2, \sigma_s^2, \sigma_c^2$ and $\sigma_{e,t}^2$ follow inverse-Gamma priors. The degrees of freedom parameter are drawn from an exponential prior, while the initial state vector follows a diffuse Gaussian distribution.

Posterior inference is conducted using a hybrid MCMC algorithm. The latent states $\{\mu_t, \beta_t, c_t\}$ are sampled using Forward Filtering Backward Sampling (FFBS), while the scaling factors λ_t are updated from conditional Gamma posteriors. The variance parameters are drawn from their inverse-Gamma posteriors, and the AR coefficients are updated conditionally as Gaussian draws with stationarity enforcement. The degrees of freedom parameter ν, which lacks conjugacy, is estimated via a Metropolis–Hastings step. This combination of Gibbs sampling and Metropolis–Hastings ensures efficient posterior exploration[10].

The MCMC draws provide posterior distributions for the key macroeconomic indicators. The trend μ_t is interpreted as potential output, while the slope β_t captures the time-varying potential growth rate. The cyclical component c_t measures the output gap, the volatility $\sigma_{e,t}$ reflects stochastic variation in measurement uncertainty, and the scaling factors λ_t highlight the occurrence of fat-tailed shocks. Together, these outputs enable a robust decomposition of GDP dynamics that accounts for structural changes, stochastic volatility, and extreme events.

3.3 Bivariate state space model

Bivariate state space model is used to jointly estimate the potential output and inflation dynamics in the presence of stochastic volatility and fat-tailed distribution. Log of real GDP is decomposed in latent trend, slope, cyclical component and a disturbance as in Univariate framework, while core inflation is modelled as function of inflation expectation and output gap along with a disturbance.

[10] The algorithm is implemented over 70,000 iterations, with the first 10,000 discarded as burn-in, resulting in 60,000 effective posterior samples.

The estimation method is similar with two measurement equations, one each for real GDP and Core Inflation[11]. The equation 3 of the univariate case is replaced by the following equations.

$$\log{(GDP)_t} = \mu_t + c_t + \varepsilon_t^{GDP}, \quad \varepsilon_t^{GDP} \sim t_{\nu_{GDP}}\left(0, \frac{\sigma_{GDP,e,t}^2}{\lambda_{GDP,t}}\right) \tag{10}$$

$$core_t = \alpha\, E_t(\pi_{t+1}) + \gamma c_t + \varepsilon_t^{core}, \quad \varepsilon_t^{core} \sim t_\nu\left(0, \frac{\sigma_{core,e,t}^2}{\lambda_{core,t}}\right) \tag{11}$$

$$x_t = [\mu_t, \beta_t, c_t, c_{t-1}]' \tag{12}$$

$$x_t = F * x_{t-1} + \omega_t, \quad \omega_t \sim N(0, Q) \tag{13}$$

Where $E_t(\pi_{t+1})$ is inflation expectation, α measure sensitivity to expectation and γ captures the impact of output gap. The transition matrix F and the innovation covariance matrix Q for the state dynamics are:

$$F = \begin{bmatrix} 1 & 1 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & \varphi_1 & \varphi_2 \\ 0 & 0 & 1 & 0 \end{bmatrix}$$

$$Q = \begin{bmatrix} \sigma_v^2 & 0 & 0 & 0 \\ 0 & \sigma_s^2 & 0 & 0 \\ 0 & 0 & \sigma_c^2 & 0 \\ 0 & 0 & 0 & 0 \end{bmatrix}$$

Similar to the univariate case, the state innovation covariance matrix Q is a diagonal matrix indicating that there is no correlation between the innovations of trend and cycle. Like the univariate case, the cyclical component also follows an autoregressive process of order two, with AR1 parameter as φ_1 and AR2 parameter as φ_2, which allows for persistence and oscillatory business cycle dynamics.

11 Core Inflation is obtained by excluding food and fuel from the headline CPI inflation.

Conditional on the scaling factors $\Lambda = \{\lambda_{GDP,t}, \lambda_{core,t}\}$, the model admits a Gaussian likelihood. The conditional density is the conditional density for both GDP and core, as in the following equations.

$$p\left(y_t^{GDP} \mid x_t, \theta, \lambda_{GDP,t} \right) = \boldsymbol{N}\left(y_t^{GDP} \middle| \mu_t + c_t, \frac{\sigma_{GDP,e,t}^2}{\lambda_{GDP,t}} \right), \tag{14}$$

$$p\left(y_t^{core} \mid x_t, \theta, \lambda_{core,t} \right) = \boldsymbol{N}\left(y_t^{core} \middle| \mu_t + c_t, \frac{\sigma_{core,e,t}^2}{\lambda_{core,t}} \right), \tag{15}$$

so that the joint likelihood is:

$$L(\theta \mid Y, X, \Lambda) = \prod_{t=1}^{T} p\left(y_t^{GDP} \mid x_t, \theta, \lambda_{GDP,t} \right) p\left(y_t^{core} \mid x_t, \theta, \lambda_{core,t} \right), \tag{16}$$

where $\theta = \{\alpha, \gamma, \phi_1, \phi_2, \sigma_{GDP}^2, \sigma_{core}^2, \sigma_v^2, \sigma_s^2, \sigma_c^2, \nu_{GDP}, \nu_{core}\}$.

The priors are like univariate case, and posteriors are estimated using MCMC with Gibbs sampling and Metropolis-hastings updates. The estimation provides a coherent framework for analysing the joint evolution of the potential output, inflation persistence and the propagation of shocks in volatile macroeconomic environment.

In the next section, we apply this framework to the empirical analysis of real GDP, presenting estimates of potential output, output gap dynamics, and volatility patterns, along with the estimation of the NKPC.

4. Empirical Findings

4.1 Univariate UCM Estimation

As discussed in the previous section, the trend and cycle of the GDP are the un-observed latent variables estimated using Bayesian Kalman Filter. The trend is modelled as the random walk with stochastic slope (representing the potential growth) and cycle is modelled as a stationary AR2 process. The irregularity is modelled as time-varying volatility with a t-distribution, characterized by low baseline volatility that spikes during irregular events such as COVID lockdowns. Figures 1 shows the estimated output gap and trend from the modified univariate Unobserved Components Model. The estimated potential growth after showing a steady rise up to 2007, has been consistently declining since 2007 after Global Financial Crisis (GFC) and then subsequent twin balance sheet problem, and reached to 5.5 percent during pandemic, after which it is increasing and currently estimated at 6.5 percent indicating sustained post-COVID recovery.

The output gap was positive in the 1997 to 2000 period. Then after 2000 (Dot com bubble bust) is started falling and went into negative territory, after that the output gap became positive just before the GFC and then after a brief fall in GFC, it recovered back to positive territory. Then post 2011, it felt close to 0, then again moved upward after 2015, peaking just before NBFC crisis of 2019. Then, during COVID it fell into negative territory in which output was below potential due to lockdowns and COVID uncertainty, which recovered close to its potential by 2023. The time-varying volatility remained range bound and low in all periods expect first lockdown in 2020 Q2 and second COVID wave 2021 Q2, where it spiked. Thus, the time varying volatility of the measurement error was able to capture the irregular spikes in the uncertainty well. Figure A2 in the appendix shows the trace plots of the coefficients of the Univariate UCM model.

In comparison to the trend cycle decomposition of GDP with traditional UCM model and HP Filter (Appendix, Figure A1 for traditional UCM decomposition model and Figure A5 for HP filter), the potential output growth is much smoother using the modified UCM approach. Similarly, extreme fluctuations in the output gap during COVID in the traditional UCM model is corrected in the modified as the output gap with modified approach remained range-bound even during COVID lockdown.

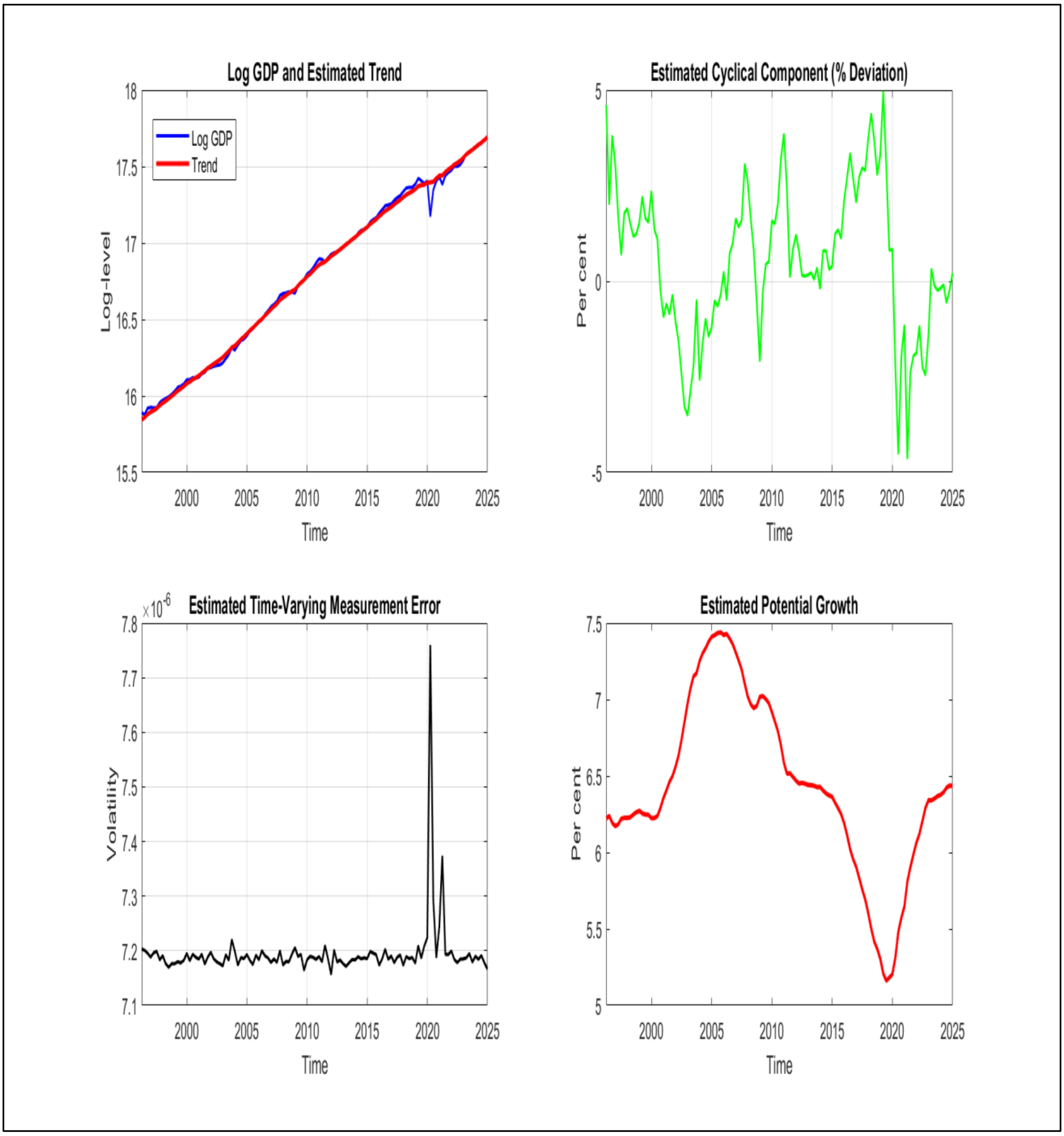


Figure 1: Output Gap estimation using univariate Kalman Filter.

4.2 Inflation Expectation Estimation

A model-based measure of expectations is constructed by regressing household inflation expectations using Polynomial (degree 2) Almon Distributed Lag model on 16 lags of core inflation and the COVID dummy D_t^{COVID}. The inclusion of the COVID dummy captures how agents updated their forecasts in real time during the pandemic. The regression shows a persistent, time-invariant gap between household inflation expectations and lagged core inflation, captured by a statistically significant constant of 3.14 (Table 1). Similarly, the highly significant positive coefficient of the COVID Dummy even in presence of 16 lags of core inflation shows that agents updated their inflation expectations in real time based on disruptions during the COVID period.

The predicted values of the inflation expectations after accounting for the constant term, serves as a more realistic proxy of forward-looking inflation expectations. It closely tracks the 4 years moving average of core inflation except during the COVID period, where there was an upward shift in the inflation expectations compared to moving average of core inflation (Figure 2).

Table 1: Regression coefficient for Inflation Expectations

Dependent Variable: 3 Months Ahead Inflation Expectation		
Time Period: 2006Q3 – 2025Q2 (Model 1)		
Variable	Coefficient	p-Value
Constant	3.14	0.000
Core Inflation PDL01	0.027	0.072
Core Inflation PDL02	-0.003	0.045
Core Inflation PDL03	0.001	0.044
COVID Dummy	2.34	0.000
R-squared: 0.60		

Core Inflation PDL01, PDL02 and PDL03 are the Polynomial Almon Distributed Lags of the Core Inflation. The model has good predictive power with R^2 of 60 %. In comparison the models, with one lag of core inflation as explanatory variable (Model 2 Table 1A, Appendix) and with four lags of core inflation (Model 3 Table 1A, Appendix), the explanatory power of model with Almon lag model is much higher, reflected in its higher R^2. This indicates that household inflation expectations are formed with much larger horizon of past realised inflation (findings are like (Chari and Misra, 2016)). Hence, there is an inertia in the inflation expectations. This has policy implication, that if the persistent high level of core inflation gets embedded in the household inflation expectations, it will not be easy to reduce it. As, the coefficients are significant with a good explanatory power, the estimated inflation expectations obtained using the model can provide a more reasonable and longer estimate of the inflation expectation.

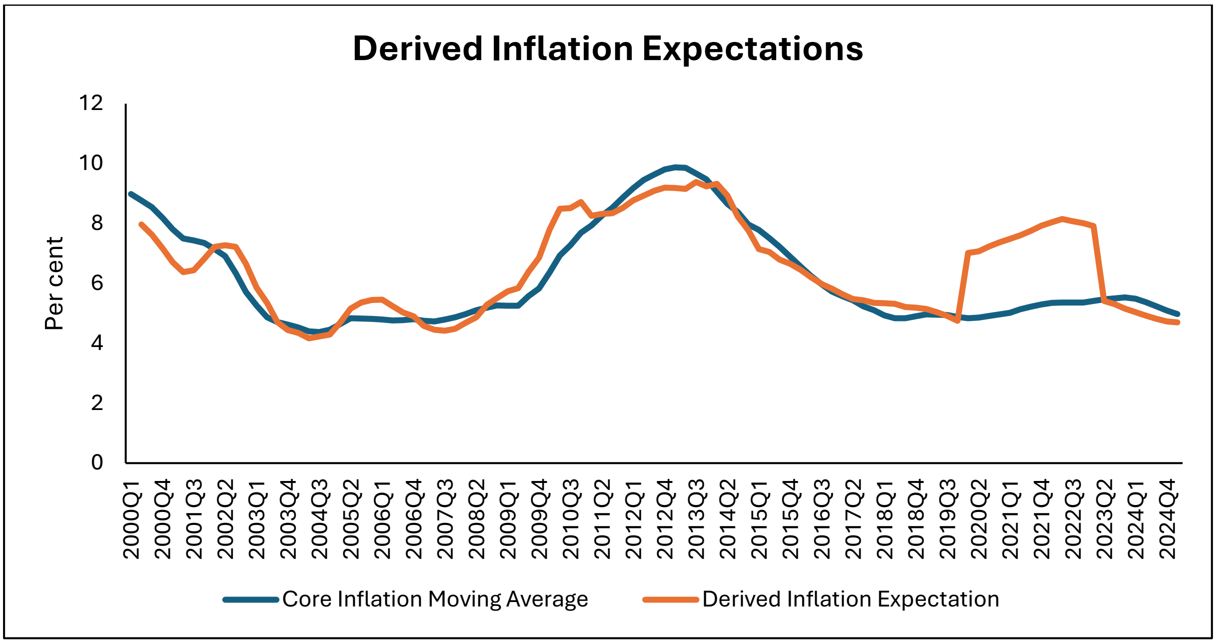


Figure 2: Estimated Inflation Expectations and 4 years Moving Average Core Inflation

4.3 Regression based NKPC Estimations

Finally, the NKPC is estimated using 2 approaches, first is the simple regression approach between the core inflation as the dependent variable and output gap (the cycle component estimated in the univariate UCM in Section 4.1) estimated from the univariate Kalman filter and inflation expectations estimated earlier as the explanatory variables. As a robustness check, the second model uses the four-year moving average of core inflation as the measure of inflation expectations. We also include an interaction between the output gap and a COVID dummy in the second model to account for the effect of temporary supply chain disruptions when expectations are backward-looking and cannot adjust in real time.

The regression estimates in Table 2, (Model 2), show that the estimated bias adjusted inflation expectations and output gap explain significant variations in the core inflation (R-square – 0.42). The estimated discount factor of NKPC is 0.89 and sensitivity of core inflation to output gap is 0.24, both coefficients are positive and significant. Similarly, the Model 1 with 16 quarters moving averages of core inflation and interaction of output gap with COVID dummy, show the similar result, as the estimated discount factor of NKPC is 0.88 and sensitivity of core inflation to output gap is 0.22, both coefficients are positive and significant. In addition, the interaction terms are negative and significant. This suggests that with backward-looking inflation expectations, where agents cannot adjust in real time, the output gap and core inflation moved in opposite directions during COVID. Temporary supply constraints from COVID restrictions pushed core inflation up even though output was far below potential. The explanatory power of the model with derived inflation expectations is more compared to backward looking inflation expectations. Bai-Perron test for structural breaks indicates that there is no breakpoint in the relationship between output gap and core inflation and Ramsay test indicates that the relationship is linear.

Now, in comparison to NKPC coefficients estimated with output gap estimated using HP Filter (Appendix, Table 2A), the sensitivity of the output gap to core inflation in the modified UCM approach is higher than output gap from HP filter, reflected in higher coefficients of the output gap in NKPC estimates. Also, the p-values of the coefficients in the case of modified UCM approach is much lower than HP filter-based output gap. This indicates the modified UCM approach of trend cycle decomposition leads to output gap estimates that is more sync with core inflation movements.

Table 2: NKPC Regression estimations

Robust HAC OLS Estimations Sample: 2000Q1–2025Q1 (Model 1) | 2000Q2 2025Q1 (Model 2)		
Variable	Model 1 Coeff. (p-value)	Model 2[12] Coeff. (p-value)
Core Inflation 16 Quarters Moving Average	0.88 ***	
Estimated Inflation Expectation		0.89 ***
Output Gap	0.22*	0.24***
Output Gap * COVID	-0.66***	
R-squared	0.19	0.43
Adjusted R-squared	0.17	0.42
Note 1: *** p-value≤0.01, ** p-value ≤0.05, * p-value ≤0.1		

[12] To check for potential non-linearity in the relationship between output gap and core inflation, we have also checked for threshold regression version of Model 2 with output gap as the threshold variable. The model found no threshold of output gap at which the relationship between output gap and core inflation changes significantly.

4.4Multi-variate UCM Estimation

The results of bivariate Kalman Filters with fat tails are shown in figure 3. The trend growth estimated using univariate and multivariate filter is similar but as figure 4 shows that both 90 percent and 68 percent credible intervals of the potential output growth (trend growth) become much narrower in bivariate case, indicating the reliability of the trend growth estimates improved significantly in the bivariate case. However, the magnitude of the variations in the output gap is lower, compared to the univariate UCM model. Also, the increase in output gap during 2019 is much less pronounced than the univariate case and unlike the univariate case the output gap is still below 0 indicating the economy has not yet recovered to the potential after COVID shock.

The estimated core inflation measure mimics the original core inflation except at the time of Global financial crisis. The volatility observed during the GFC in the inflation is captured as time varying measurement error, whereas, for GDP, there are several episodes of volatility being captured in the time varying measurement error. In terms of coefficients of the NKPC coefficients of second measurement equation, shown in the Figure A3 Appendix, show that the NKPC coefficients obtained using this multivariate method are consistent with those from regression estimation.

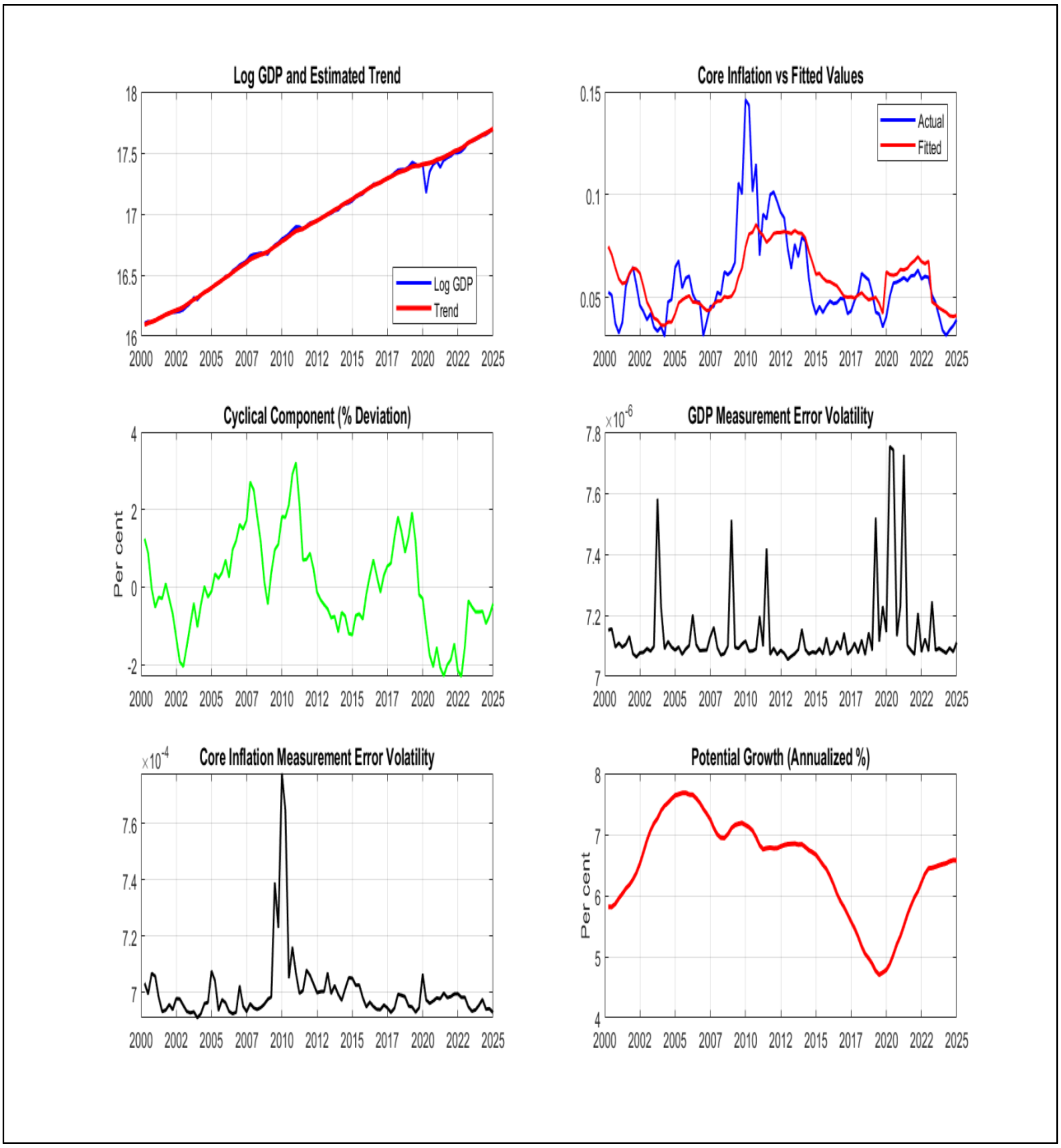
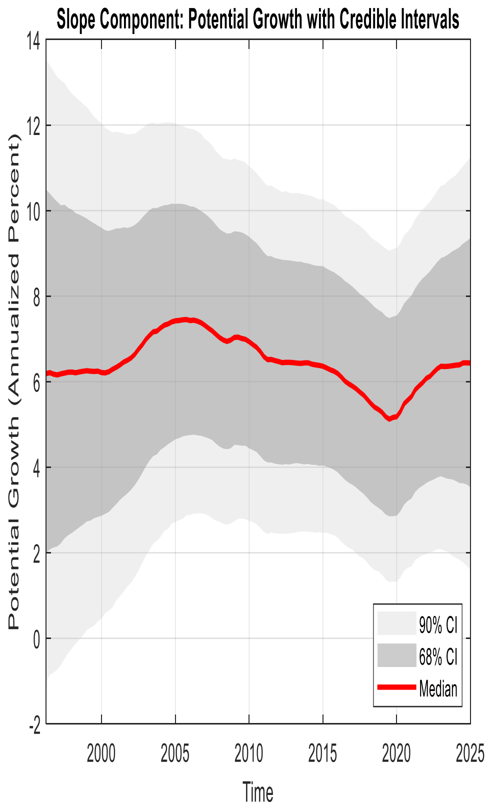


Figure 3: Output Gap estimation using multivariate Kalman Filter

Potential Growth (%) Univariate UCM	Potential Growth (%) Bivariate UCM



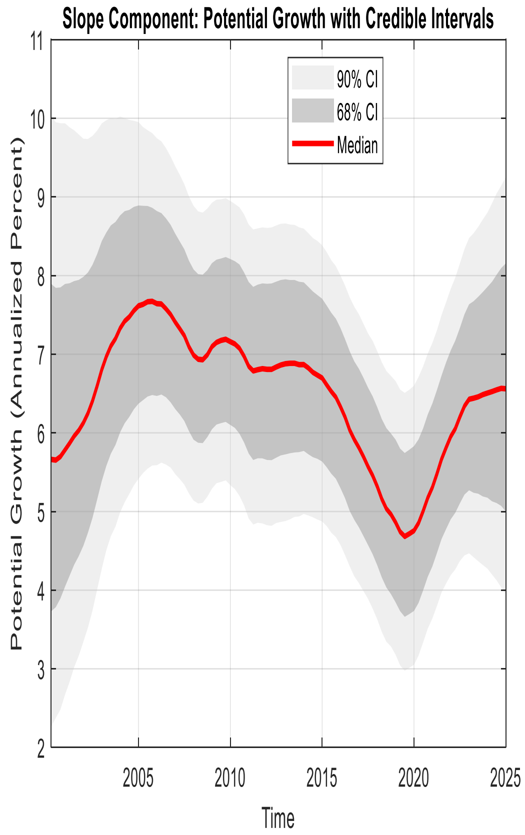


Figure 4: Potential Growth with credible intervals

5 Conclusion

This study underscores the importance of adapting the New Keynesian Phillips Curve (NKPC) framework to account for large-scale disruptions such as the COVID-19 pandemic. By introducing a fat-tailed error structure in the Kalman filter and adjusting the measure of inflation expectations through a model-based proxy, the framework effectively isolates transitory shocks without distorting the underlying estimates of potential output and inflation dynamics. This approach improves the robustness of output gap estimation and provides a more accurate assessment of inflation expectations in times of heightened uncertainty.

Empirical findings demonstrate that household inflation expectations in India are characterized by a persistent time-invariant upward gap with core inflation, while extraordinary shocks like COVID-19 amplifies short-term deviations. By accounting for these irregularities, the revised estimates better capture the forward-looking nature of inflation. expectation formation. The results from both regression using the estimates of output gap from the univariate and multivariate Kalman filter decomposition yield consistent NKPC parameters, reaffirming the forward-looking discount factor and sensitivity of inflation to output gap. By combining a modified output gap estimation technique with a more realistic expectation formation process, it enhances the reliability and interpretability of inflation dynamics.

The research in future can be extended to the estimation of hybrid NKPC as, a hybrid version of the NKPC that incorporates both forward- and backward-looking inflation expectations to account for the adaptive nature of household expectations, has been found to be empirically more robust.

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Appendix

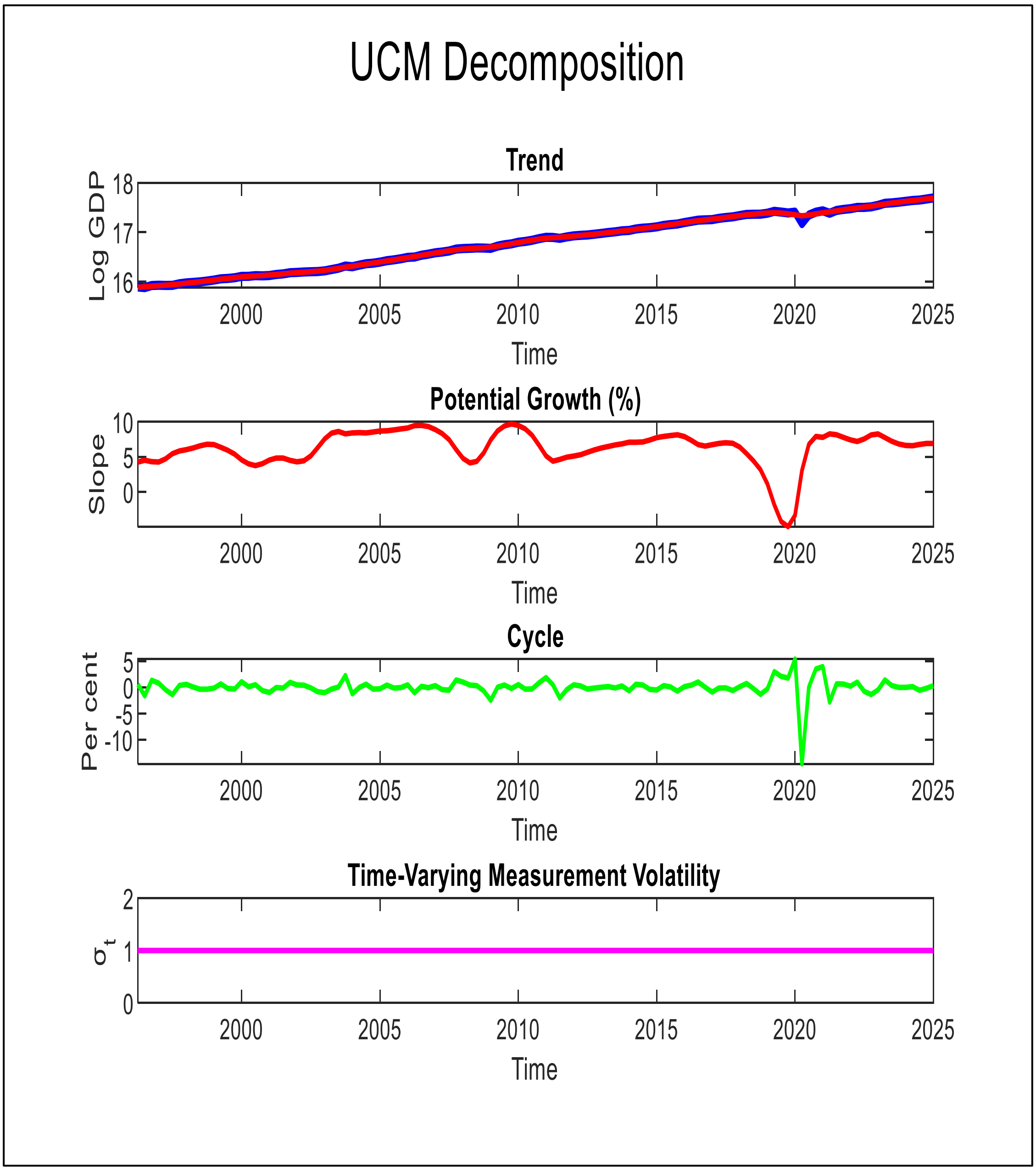


Figure A1: Univariate UCM model without time-varying volatility

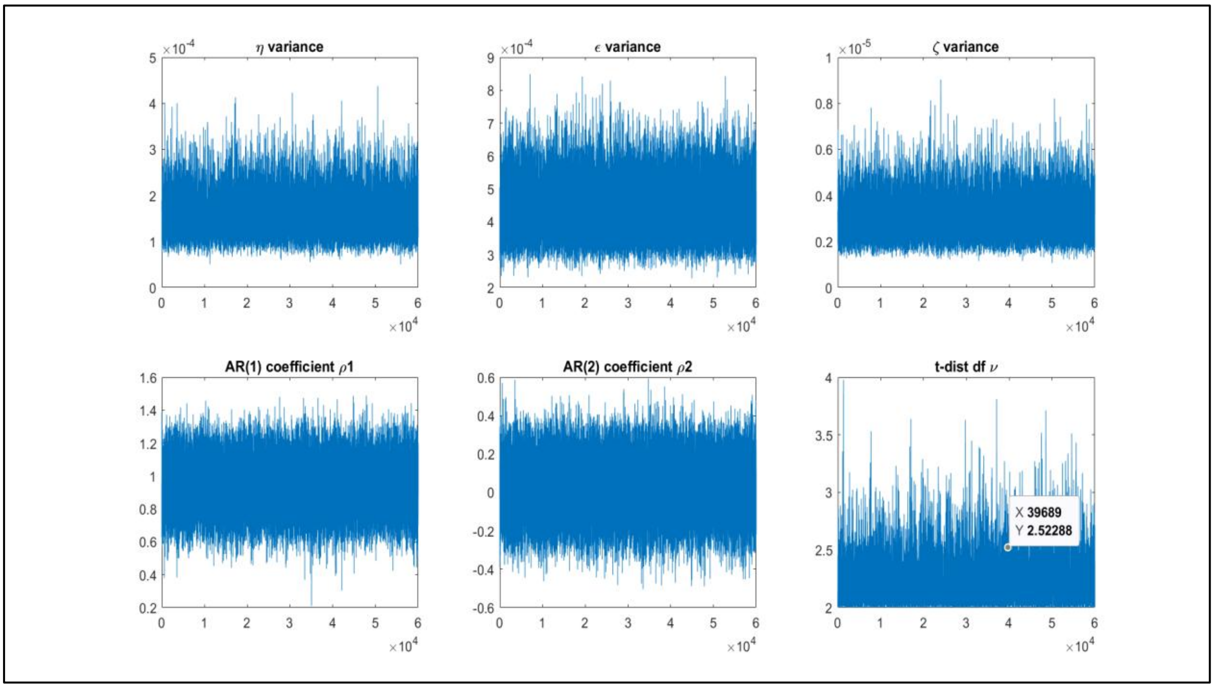


Figure A2: Trace Plots of the coefficients of univariate UCM mode

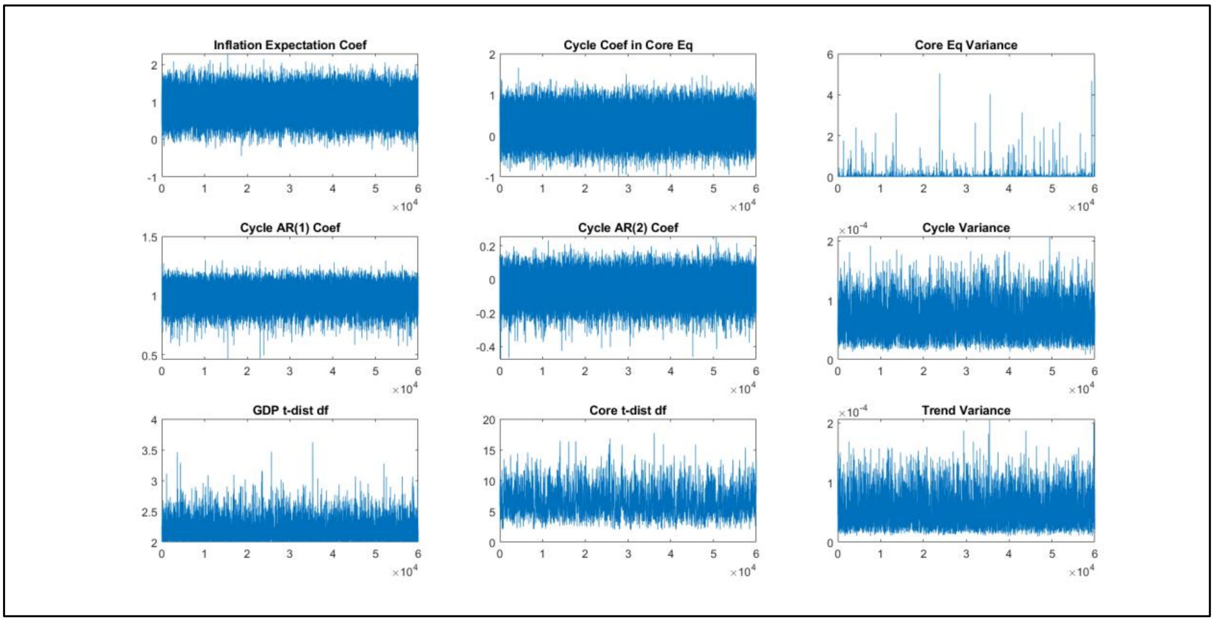


Figure A3: Trace Plots of coefficients of bi-variate UCM model

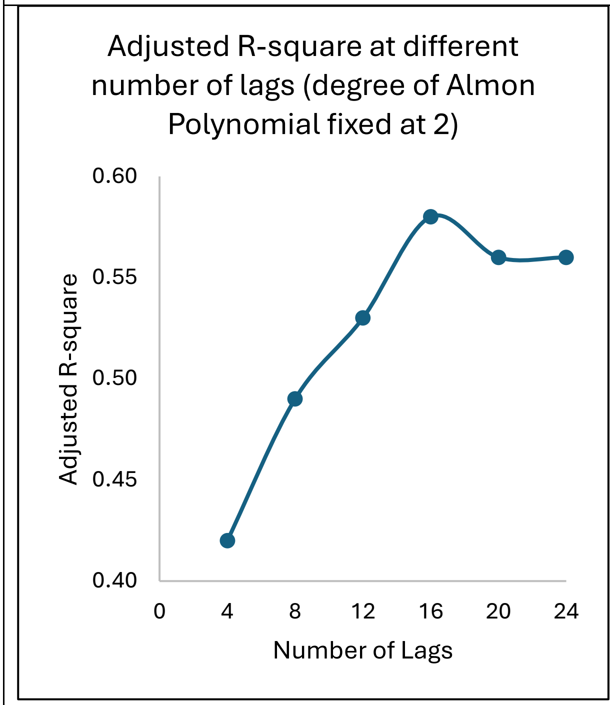
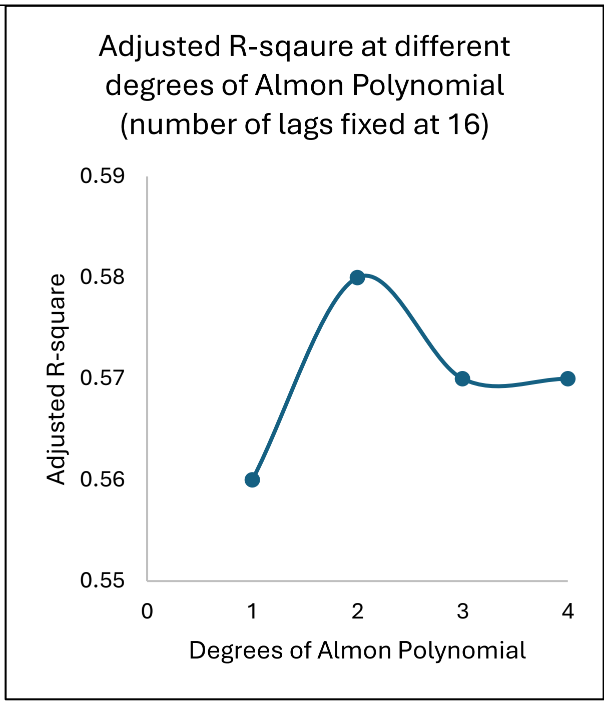
Adjusted R-square at different number of lags	Adjusted R-square at different number of lags
	

Figure A4: Adjusted R-square at different lags and degrees of Almon Polynomials

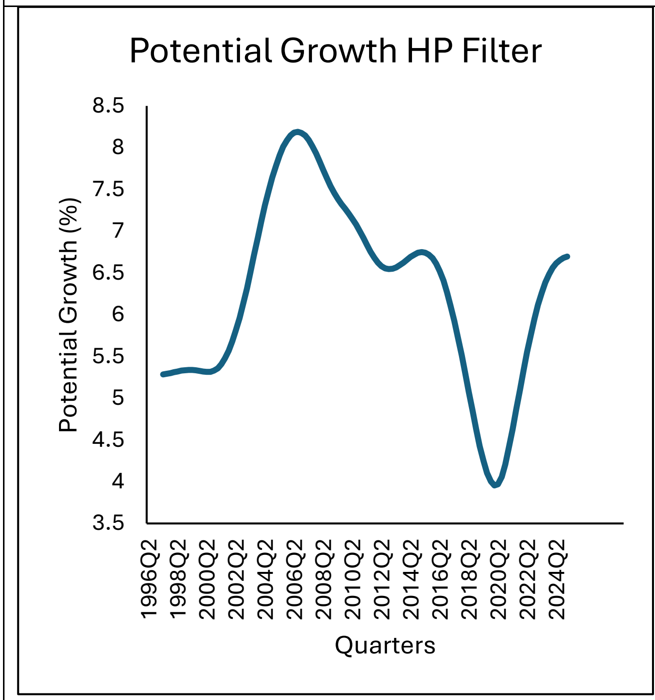
Table 1A: Inflation Expectation explained by lags of core inflation

Sample: 2006Q3–2025Q1 (Model 1) | 2006Q3 2025Q1 (Model 2) (Dependent Variable – Household Inflation Expectations		
Variable	Model 2 Coeff.	Model 3 Coeff.
Constant	6.43***	5.59***
Core Inflation (-1)	0.50***	0.35**
Core Inflation (-2)		-0.02
Core Inflation (-3)		-0.09
Core Inflation (-4)		0.39***
Covid	1.56***	1.82***
R-squared	0.38	0.46
Adjusted R-squared	0.36	0.42
Note 1: *** p-value≤0.01, ** p-value ≤0.05, * p-value ≤0.1		

Table 2A: NKPC Estimation with HP Filtered Output Gap

Robust HAC OLS Estimations, Sample: 2000Q1–2025Q1 (Model 1) | 2000Q2 2025Q1 (Model 2)		
Variable	Model 1 Coeff. (p-value)	Model 2[13] Coeff. (p-value)
Core Inflation 16 Quarters Moving Average	0.88 ***	
Estimated Inflation Expectation		0.90 ***
HP Filter Output Gap	0.1	0.1**
HP Filter Output Gap * COVID	-0.91***	
R-squared	0.18	0.40
Adjusted R-squared	0.17	0.39
Note 1: *** p-value≤0.01, ** p-value ≤0.05, * p-value ≤0.1		

HP Filter derived Potential Output Growth	HP Filter derived Output Gap



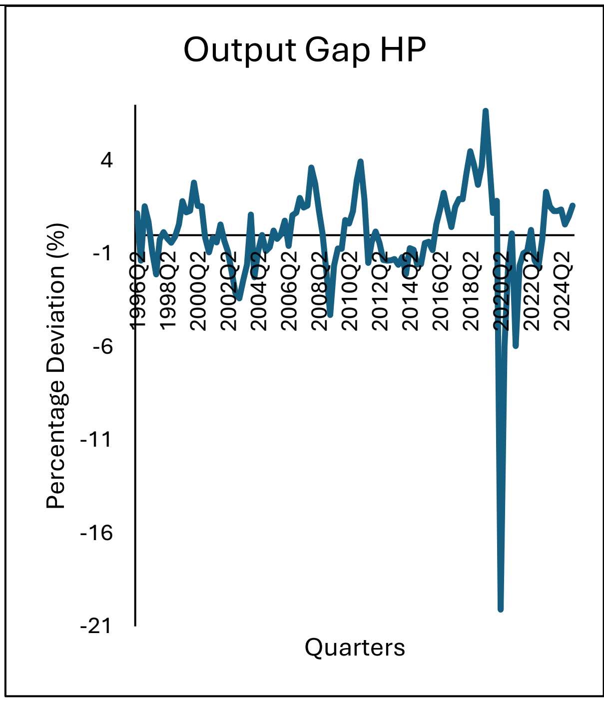


Figure A5: Potential Output Growth and Output Gap using HP Filter

[13] To check for potential non-linearity in the relationship between output gap and core inflation, we have also checked for threshold regression version of Model 2 with output gap as the threshold variable. The model found no threshold of output gap at which the relationship between output gap and core inflation changes significantly.