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Is the impact of Covid-19 pandemic on real output growth of India transitory or permanent?

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Abstract

In this study, we intend to analyze whether the impact of COVID-19 on the real output growth of India was permanent or transitory by decomposing the real GVA growth rate in India into trend and cyclical components using three statistical filters: Hodrick–Prescott filter, Christiano–Fitzgerald filter, and univariate Kalman filter. The measure of real output in India is determined using real Gross Value Added (GVA). In our analysis, the annual data on real GVA at 2011-12 base is sourced from the Central Statistical Organisation, MOSPI, GOI. We observe the fluctuation in the cyclical component due to pandemic shock significantly exceeds the trend component. We also observe that the post-COVID average trend growth, which dipped drastically during the pandemic, started to catch up quickly with the pre-COVID decadal average trend growth. Our findings suggest that the shocks due to the COVID-19 pandemic on India's real output growth were more of a transitory nature.

JEL Classification: E32, C32, E01, O47, I15

Keywords: COVID-19, real output growth, statistical filters, India

1. Introduction

The emergence of the worldwide pandemic led to unprecedented shocks in the global economy. The world was still recovering from the Great Recession of 2008-09 before it was hit by yet another crisis, this time a global health crisis. Various governments implemented stringent policies of lockdown and social distancing to protect civilians to ensure public health and safety. Movement of people and goods was put to a halt, and a worldwide emergency was declared. Bajra et al. (2023) demonstrate a negative relationship between policy stringency and GDP growth. The global economy shrank by 3.5% in 2020, compared to the 3.4% growth that was projected in October 2019. The advanced economies experienced a contraction of 4.7%, while the emerging market and developing economies contracted by 2.2% (International Monetary Fund [IMF], 2021). India was experiencing a decelera- tion in real growth rate from 2017-18 due to the accumulated and lagged impacts of domestic and global macroeconomic shocks including Demonetization (2016-17), implementation of Goods and Services Tax (GST) system (2017-18) and trade conflicts between US and China (Bhattacharya and Prasanth, 2024). India's real GDP dipped to its bottom in over six years during Q4 2019-20 (Das and Patnaik, 2020). With the onset of the COVID-19 pandemic, India's annual GDP growth rate contracted by 5.8% in 2020-21. Over 120 million individuals in India have been plunged into poverty as a result of the COVID-19 pandemic (Junuguru and Singh, 2023). Hence, it is natural to ask if the adverse impact on the economy due to the pandemic is permanent or temporary.

In this study, we intend to analyze whether the impact of COVID-19 on the real output growth of India was permanent or transitory by decomposing the real GVA growth rate in India into trend and cyclical components using different statistical filters: Hodrick–Prescott filter, Chris- tiano–Fitzgerald filter, and univariate Kalman filter. A permanent shock would significantly affect the trend growth, while a transitory shock would drive short to medium-term fluctuations of the growth rate around the trend growth. Nelson and Plosser (1982) point out that secular movements need not be modeled by a deterministic trend, and detrending, in such cases, by regression on time may result in misspecified residuals. Therefore, we employ filter-based methods to decompose the time series data into trend and cyclical components.

We observe the fluctuation in the cyclical component due to pandemic shock significantly exceeds the trend component. The dip in Gross Value Added

(GVA) trend growth in 2020 relative to the pre-COVID decadal average are 0.36, 0.42, and 0.77 in fractional terms, as calculated using the HP (Hodrick-Prescott), CF (Christiano-Fitzgerald), and Kalman filters, respectively. However, the cyclical component of GVA growth experienced a much larger decline, with drops of 25.78, 23.14, and 24.50 in fractional terms according to the same filters, approximately 100 times larger in magnitude than the fluctuations in the trend component. We also observe that the post-COVID average trend growth, which dipped drastically during the pandemic, started to catch up quickly with the pre-COVID decadal average trend growth. The post-COVID average trend growth is 0.03 and 0.09 lower than the pre-COVID decadal average in fractional terms, as per the HP and CF filters, respectively. Notably, the Kalman filter suggests that post-COVID average trend growth has surpassed the pre-COVID decadal average trend growth by 0.03 fractional points. Our findings suggest that the shocks due to the COVID-19 pandemic on India's real output growth were more of a transitory nature. In section 2, we go over relevant approaches and undertake a quick overview of the literature. We give a brief overview of the three filters—the HP, CF, and Kalman filters—in section 3. We review the empirical findings in section 4 before wrapping up in section 5.

2. Literature Review

Mann (2020) posited that the crisis's adverse effects on the global economy would persist, resulting in a recovery trajectory for the global economy that is more akin to a U shape rather than a V shape. Cerra et al. (2021) also argues that the large-scale unemployment and fall in output due to the COVID-19 pandemic can leave long-term scars on the economy, also known as hysteresis. Noy et al. (2020) argue that the economic risk posed by COVID-19 is highest in the poorest parts of South Asia and Sub-Saharan Africa. They assess the economic risk of COVID-19 in developing nations by utilizing pre-pandemic data sources. Approximately 22% of the total global loss is experienced by developing Asian economies. This loss is estimated to be between $1.3 trillion and $2.0 trillion, which accounts for 5.7% to 8.5% of developing Asia's GDP (Abiad et al., 2020). Emerging markets are, therefore, expected to be more vulnerable to these scars than advanced economies. According to Aguiar and Gopinath (2007), the main cause of fluctuations in emerging markets is not shocks to transitory fluctuations around a stable trend but rather the shocks to trend growth due to frequent changes in monetary, fiscal, and trade policies. This raises the question of whether the fluctuations in emerging nations like India due to the COVID-19 shock were caused by a shock to the trend or transitory fluctuations. Iswahyudi et al. (2021) demonstrates that in the case of Indonesia, an emerging market, the impact of the pandemic is likely to have a long-lasting effect on the country's economic output and fiscal capacity, leading to a persistent decline. According to Jackson and Lu (2023), COVID-19 had a material and persistent impact on economic activity. However, they also note that the recovery has been more robust and faster than expected. They find that forecasts of scarring have increasingly treated positive data surprises as transitory rather than as a signal about the extent of scarring.

In order to ascertain whether the impact of COVID-19 was temporary or permanent, we aim to compare the degree of fluctuations in the trend and cyclical components of real output growth. Therefore, we will look at the methodologies researchers use to decompose a time series into its trend and cyclical component. The trend and cyclical components of output growth refer to the potential growth rate, i.e., growth in potential output and the transitory fluctuations around it, respectively. The potential output is defined as the highest level of output that can be generated without causing inflationary pressures or the highest level of output that is sustainable in the long term. Bhoi and Behera (2017) broadly classify the methods used by researchers to estimate the potential output into three categories:

a. Purely statistical methods, such as deterministic trend removal, Hodrick-Prescott (HP) filter, Band pass filters like Baxter-King (BK) filter and Christiano-Fitzgerald (CF) filter, univariate Kalman filter, etc.

b. Methods combining structural relationships with statistical methods, such as the multivariate Kalman filter.
c. Structural models based on economic theory, such as the production function approach.

Statistical methods are favored due to their straightforward implementation and reduced reliance on extensive data, often scarcely available in emerging markets and low-income countries. The use of structural methods, such as the production function approach, provides the most reliable estimation of potential output due to its utilization of economic theory and reliance on extensive data regarding factors of production and output. Although statistical methods are mechanical and less robust than structural methods, macroeconomists widely utilize them.

Now, we will present a few instances in a global and Indian context, employing various methodologies to calculate potential output and output gaps. Cerra and Saxena (2000) utilized both the Univariate Unobserved Components (UUC) and Multivariate Unobserved Components (MUC) models to calculate the output gap for Sweden. Llosa and Miller (2005) employ a MUC model to calculate the Peruvian output gap. They rely on an explicit short-term relationship between the output gap and inflation rate (the Phillips Curve) and impose structural constraints on output dynamics. Blagrave et al. (2015) present calculations of potential growth and output gaps for 16 countries using the multivariate filter created by Beneˇs et al. (2010). Bordoloi et al. (2009) uses statistical and econometric methods like UUC, MUC, Structural Vector Autoregression (SVAR), Beveridge-Nelson (BN) Decomposition, HP filter, and bandpass filters to estimate potential output in India. Bhoi and Behera (2017) employ the production function approach, BN Decomposition, and filters like the Kalman filter, HP, BK, and CF filter to assess the potential output and output gap. Iswahyudi et al. (2021) uses a different approach to determine whether shocks are temporary or permanent by examining unit root presence in GDP, income tax revenue, VAT revenue, income tax-to-GDP ratio, and VAT-to-GDP ratio time series data.

3. Data and Methodology

The measure of real output in India is determined using real Gross Value Added (GVA). For this analysis, annual data on real GVA, based on constant prices (2011-12 base year), has been obtained from the Central Statistical Organisation (CSO), Ministry of Statistics and Programme Implemen- tation (MOSPI), Government of India (GOI). Our dataset spanning the period 1980-81 to 2023-24 includes GVA at factor cost of old bases converted to 2011-12 base year as sourced from the Economic and Political Weekly Research Foundation India Time Series (EPWRFITS) database. Following is a brief account of the three statistical filters: Hodrick–Prescott (HP) filter, Christiano–Fitzgerald (CF) filter, and univariate Kalman filter used for trend-cyclical decomposition of real output growth to compare the degree of fluctuations due to COVID-19 shock.

a. Hodrick – Prescott (HP) filter

Hodrick and Prescott (1997) propose a conceptual framework that a given time series x_t can be decomposed into a trend component x_t^g and a cyclical component x_t^c.

$$x_t = x_t^g + x_t^c, \qquad \forall t = 1, 2, \ldots, T \tag{1}$$

HP filter smoothens the time series by an optimization problem, requiring minimizing the sum of the squared gap between the long-run trend and actual time series and the sum of the square of the second-order difference in the long-run trend.

$$\min_{\{x_t^g\}_{t=1}^T} \left\{ \sum_{t=1}^{T} \left[\left(x_t - x_t^g\right)^2 + \lambda\left(x_t^g - 2x_{t-1}^g + x_{t-2}^g\right)^2 \right] \right\} \tag{2}$$

The smoothing parameter, λ, determines the smoothness of the long-run trend. Hodrick and Prescott (1997) advise taking the value of λ as 1600 for quarterly data. Moreover, Ravn and Uhlig (2002) recommend taking the value of λ as a multiplication of 1600 and the fourth power of the change in frequency of the observation, which for annual observations equals 6.25 $\left(= 1600 \cdot \left(\frac{1}{4}\right)^4\right)$. (2002) recommend taking the value of as a multiplication of 1600 and the fourth power of the change in frequency of the observation, which for annual observations equals 6.25.

b. Christiano–Fitzgerald (CF) filter

The Christiano–Fitzgerald (CF) filter is a band pass filter that separates business cycles from time series data by eliminating very low and high-frequency cycles from the actual series. For an infinitely long time series x_t, we can obtain the cyclical components x_t^* by passing it through an ideal band pass filter:

$$x_t^* = \sum_{j=-\infty}^{\infty} b_j \, x_{t-j} \tag{3}$$

Where the weights b_j of the ideal band pass filter are given by,

$$b_0 = \frac{1}{\pi}(\omega_M - \omega_m) \quad \text{and} \quad b_j = \frac{1}{\pi j}\{\sin(\omega_M j) - \sin(\omega_m j)\}, \forall j \neq 0 \tag{4}$$

Taking $\boldsymbol{\omega_m = \frac{2\pi}{T_m}}$ and $\boldsymbol{\omega_M = \frac{2\pi}{T_M}}$ gives,

$$b_0 = 2\left(\frac{1}{T_M} - \frac{1}{T_m}\right) \text{ and } b_j = \frac{1}{\pi j}\left\{\sin\left(\frac{2\pi j}{T_M}\right) - \sin\left(\frac{2\pi j}{T_m}\right)\right\}, \forall j \neq 0 \tag{5}$$

This ideal band pass filter extracts the cyclical components of frequency in the range, $\omega_m \leq \omega \leq \omega_M$, from the given time series. Here, T_M and T_m denote the maximum and minimum duration of the business cycle. Since time series are not infinite in reality, it is not possible to calculate the ideal band pass filter. Baxter and King (1999) solves for an optimal approximating filter which requires a maximum lag and lead of length K with the weights: $a_j = b_j - \theta$ where, $\theta = \frac{b_0 + 2\sum_{j=1}^{K} b_j}{1+2K}$ and b_j is given by equation (5). The optimal approximating filter gets close to the ideal filter with increasing K but at the cost of increasing the number of missing observations at the start and end of the filtered series, amounting to $2K$ missing data points. The problem of missing points hinders the analyses that involve studying the data at the endpoints of the filtered series. Christiano and Fitzgerald (2003) proposes an alternative approximate band pass filter while addressing this issue:

$$x_t^* = \sum_{j=t-T}^{t-1} c_j \, x_{t-j} \tag{6}$$

Where the weights c_j are given by,

$$\begin{aligned} c_{t-1} &= \tfrac{1}{2} b_0 - \textstyle\sum_{k=0}^{j-1} b_k, \\ c_j &= b_j, \forall j = t-2, \ \ldots, \ t-T-1 \\ c_{t-T} &= \frac{1}{2} b_0 - \sum_{k=j+1}^{0} b_k \end{aligned} \tag{7}$$

$\forall t = 1, \ \ldots, \ T$ and the weights b_j are given by equation (5).

Based on the definition given by Burns and Mitchell (1946), business cycle refers to fluctuations in economic data lasting between six and thirty-two quarters. For our annual data, we take the minimum and maximum periods T_m and T_M to be 2 and 8, respectively.

c. Kalman filter

The state-space form is employed to calculate the log-likelihood of the observed endogenous variables, given their own previous values and any exogenous variables. The Kalman filter is applied to recursively predict the current values of the states and endogenous variables. To decompose the real output growth into trend and cyclical components, we use the following specifications:

$x_t^o = x_t^l + x_t^c + \epsilon_t^o$	(8)
$x_t^l = \mu + x_{t-1}^l + \epsilon_t^l$	(9)
$x_t^c = \rho x_{t-1}^c + \epsilon_t^c$	(10)

Where, $|\rho| \leq 1$. x_t^o, x_t^l, and x_t^c are observed growth rate, long-run growth rate, and cyclical growth rate of GVA, respectively. x_t^l and x_t^c are unobserved state variables and x_t^o is the observed dependent variable. ϵ_t^o, ϵ_t^l, and ϵ_t^c are independent Gaussian white noise processes. We fit the long-run growth rate to a random walk process and the cyclical component to an AR (1) process. The covariance structure for the errors in the state variables is assumed to be diagonal because we assume independence among the state errors, implying zero covariance between them.

We predict the unobserved states from the state-space model using smoothed prediction, which incorporates all available sample information. This method is useful for examining underlying trends as it provides the most accurate estimates of the states. Alternatively, the unobserved states can also be predicted using the one-step ahead method, which makes predictions at each point in time using only the information available up to that point. This method is particularly useful for forecasting future values and is relatively less accurate. For this project, since the aim is to study the nature of the impact of COVID-19 on India's real output growth, using smoothed prediction is more appropriate. We add a constraint to fix the ratio m between the variances of ϵ_t^l and ϵ_t^c:

$m = \frac{\sigma_l^2}{\sigma_c^2}$	(11)

We estimate the parameters of the above state-space model for different values of $m \in \{0.01, 0.1, 0.5, 1, 2, 3, 5, 10\}$. Our goal is to identify the value of m that best fits the state-space model by meeting the following criteria:

- The RMSE value between the predicted and observed GVA growth rate should be less than 0.5
- According to the Wald test, the estimated coefficients of the state variables and the lagged state variables of the model should be significant at least at 10% level

4. Results

In this study, we decomposed the real GVA growth rate into trend and cyclical components using statistical filters to compare the degree of fluctuations due to COVID-19 shock. The implementation of HP and CF filters was straightforward. However, for the Kalman filter, we need to decide the value of m that satisfies the two aforementioned conditions. Table 1 summarizes the root mean square error (RMSE) and p-values corresponding to various values of m. The value of m = 2 fulfills both of the aforementioned conditions.

$\boldsymbol{m = \frac{\sigma_l^2}{\sigma_c^2}}$	RMSE	Prob > chi2
0.01	0.44	0.97
0.1	0.45	0.92
0.5	0.47	0.55
1	0.48	0.29
2	0.49	0.09
3	0.5	0.03
5	0.51	0.006
10	0.52	0.0003

Table 1: Results of RMSE and Prob > chi2 for different values of m

Upon estimating the parameters of the above state space model while taking $m = 2$, the maximum log-likelihood comes out to be -102.47. The estimated auto-regressive coefficient ρ comes out to be -.43 and the null-hypothesis of its being zero is rejected at a significance level corresponding to a 10% p-value. The variances of the errors of the observed and state variables, σ_O^2, σ_l^2, and σ_C^2 are 0.25, 2.55, and 1.27, respectively. Figures 1 and 2 display the filtered trend growths and the corresponding cyclical components for each filter.

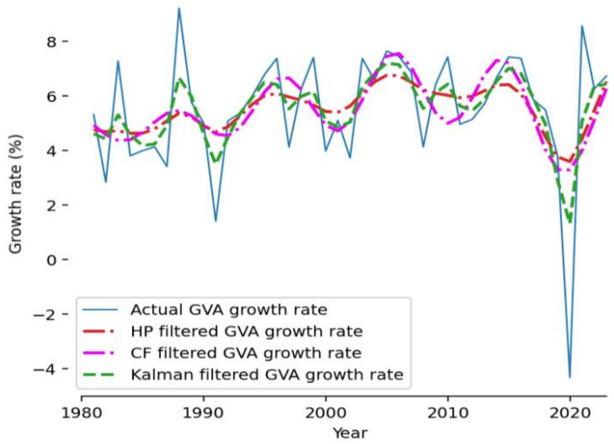

Figure 1: Trend components of real GVA growth rate

To determine whether the effects of COVID-19 were temporary or permanent, we compare the extent of variations in the trend and cyclical components of real output growth. We compare the shock on the trend and cyclical growth of GVA in 2020 due to COVID-19 to the average growth rate observed during the previous decade (2010-2019). This comparison is presented in Table 2, as referenced by (12) and (13).

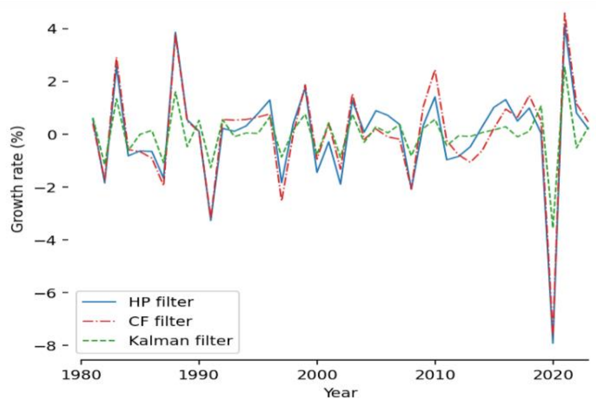

Figure 2: Cyclical components of real GVA growth rate

$$\Delta Trend\ growth_{2020} = \frac{Trend\ growth_{2020} - Avg\ trend\ growth_{2010-19}}{Avg\ trend\ growth_{2010-19}} \quad (12)$$

$$\Delta Cyclical\ growth_{2020} = \frac{Cyclical\ growth_{2020} - Avg\ cyclical\ growth_{2010-19}}{Avg\ cyclical\ growth_{2010-19}} \quad (13)$$

Filter	$\Delta Trend\ growth_{2020}$	$\Delta Cyclical\ growth_{2020}$
HP	-0.36	-25.78
CF	-0.42	-23.14
Kalman	-0.77	-24.50

Table 2: Comparison of Trend and Cyclical Growth Rates of Gross Value Added (GVA) in 2020 with the Decadal Average (2010-2019)

We observed that the size of the cyclical growth fluctuations was significantly greater than trend growth. This suggests that the COVID-19 shock on real GVA growth had a more transitory impact (cyclical) than long-term trends.

We also assess whether the trend growth following COVID-19 has approached the average trend growth of the previous decade to make observations about the recovery after the pandemic. A faster recovery would suggest that the COVID-19 shock on real GVA growth had a transitory impact. We compare the average trend growth of the three years post-COVID (2021-2023) to the average trend growth observed during the previous decade (2010-2019). This comparison is presented in Table 3, as referenced by (14).

$$\Delta Trend\ growth_{post-COVID} = \frac{Avg\ trend\ growth_{2021-23} - Avg\ trend\ growth_{2010-19}}{Avg\ trend\ growth_{2010-19}} \quad (14)$$

Filter	$\Delta Trend\ growth_{post-COVID}$	$\Delta Trend\ growth_{2020}$
HP	-0.03	-0.36
CF	-0.09	-0.42
Kalman	0.03	-0.77

Table 3: Comparison of Post-COVID Average Trend Growth (2021-2023) with Pre-COVID Decadal Average Trend Growth (2010-2019)

We observe that the difference between the post-COVID average trend growth and the pre-COVID decadal average has reduced significantly compared with the fluctuation in trend growth in 2020. In fact, according to the Kalman filter, the post-COVID average trend growth has exceeded the pre-COVID decadal average. However, the HP and CF filters indicate that while the post-COVID average trend growth is still lower than the pre-COVID decadal average, the gap has reduced significantly, indicating a speedy recovery.

5. Conclusion

In this study, we employed three statistical filters—the Hodrick–Prescott (HP) filter, the Christiano–Fitzgerald (CF) filter and the univariate Kalman filter—to decompose the economic shocks caused by the COVID-19 pandemic into trend and cyclical components in order to determine whether the impact was permanent or transitory on India's GVA growth rate. We observe that the fluctuation in the cyclical component due to pandemic shock significantly exceeds the trend component. We also gather that the post-COVID average trend growth, which dipped drastically during the pandemic, started to catch up quickly with the pre-COVID decadal average trend growth. Moreover, the results from the estimation of the Kalman filter show that the post-COVID average trend growth has exceeded the pre-COVID decadal average trend growth. Our findings suggest that the shocks due to the COVID-19 pandemic on India's real output growth were more of a transitory nature, agreeing with the results of Jackson and Lu (2023), who also noted that the recovery in emerging markets has been more robust and faster than expected.

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