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An Empirical analysis of Rising Food Inflation using VAR approach

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Abstract: The paper underscores an empirical investigation into the rising food inflation in India based on the Vector Autoregression (VAR) technique, for the period from 1992 to 2021. The paper identifies an important economic issue in India, whereby food price inflation has been recognized as a major concern, especially in the wake of the increase in average food inflation of above 80% relative to inflation in other non-food items in the period from 2006-2009. The investigation assumes its importance in the wake of the COVID-19 crisis, which initiated parallel forces, such as the contraction in economic activities following the imposition of lock downs, and as such, triggered food inflation in the economy. The paper uses secondary data collected from various publications, such as the Handbook of Statistics on India Economy and the publications of the Economic Survey of India in 2021, as well as databases like FAOSTAT and the International Monetary Fund. The investigation develops two VAR frameworks in uncovering the variables that influence food inflation in the economy.

Introduction

Over the years, especially from 2005 onward, the increase in food prices has been considerably greater than that in non-food prices, except in the year 2008 when world commodity prices escalated in India as well as across the world. From 2006 to 2009, the average food inflation rate was more than 80% higher than the inflation rate in non-food items. **(Rames Chand,2010)**. The rising food prices form a major economic concern in the current state of the country, and the ability of the Government to control food prices is likely to be an important determining criterion for public perception about its performance. The last decade has witnessed the control over food prices emerge as an important challenge for the developing nations. The early phases of the rising food prices identified several macro-economic factors like supply constraints, devaluation of the dollar, rise in governmental expenditure, and flexible monetary policy that contributed to food price inflation across the world. **(*Baffes & Haniotis,* *2010).***

With the global pandemic of Covid-19 causing social estrangement and interrupting global economic activity, the year afterwards 2019 was unique in itself. On national level, two competing forces doing their work rigoursly. One side, there is decreasing economic activity due to restrictions imposed during lockdown, resulted in lack of demand. On the other side, supply chain disruptions have resulted in food inflation surges that have persisted throughout the unlocking process of the Indian Economy. The COVID-19 outbreak has already become a serious threat to public health, leading countries worldwide to impose partial economic shutdowns to mitigate further spread of the virus. The aforementioned measures have already led to serious disruptions in the global and regional supply chains. The strict lockdown or, conversely, the prolonged outbreak might affect food supplies in

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different ways. Firstly, the effect is likely to be the following. Second it might affect the availability of packaged goods from food-processing industries, given the slowdown in manufacturing due to the lack of social distancing. Secondly, it could imply a reduction in crop output in the coming years, given the diminished income.

There is ample literature suggesting three primary reasons for high food inflation: rising food production costs, lifestyle changes, and government policies. ***(Gulati et al., Gulati & Saini, 2013; Gokarn, 2011; Bandara,2013; Gulati & Shweta 2013; Ganguly & Gulati, 2013)*** India, being a developing country, has observed changes in food habits, with diets gradually shifting from calorie-rich cereal-based foods to nutrient-rich foods such as pulses, milk products, eggs, meat, fish, and vegetables, ultimately leading to price escalation of these commodities **(*Gokarn, 2011; Bandara, 2013; Gulati & Saini, 2013)***. Progressive deregulation of administered fuel prices in India will likely continue to pass on rising fuel costs to fertilizer and transportation costs, thereby pushing up food inflation **(*Bandara, 2013; Bhattacharya & Sen-Gupta, 2018)***. The COVID-19 recession is projected to have led to an increase of 75 million people living on $2 or less a day in India. It accounts for almost 60% of the worldwide increase in poverty. An increase in food prices also impacts the lives of people living with extreme poverty, such as those who lived in India between 1992 and 2021, as they spend a large amount of money on food, leaving them with no means to spend more on it despite its increasing price.

Inflation is an important tool that provides crucial information and insight into the economic conditions and effective macroeconomic policies prevailing within the economy. By keeping inflation within controlled limits, it not only enables a supportive environment within which economic growth can flourish but also protects low-income classes and fixed-income earners, who are most vulnerable within society. The government has to be careful about inflation and has taken various steps to ease demand pressures while boosting the supply side at the same time.

Rising prices will probably accelerate further with escalating tensions in Ukraine, comprising escalating commodity prices, along with an increase in fuel prices for transportation, which have been paused for over four months due to assembly elections in five states, according to analysts. An increase in retail inflation is slightly more than what has been estimated by a Bloomberg survey of economists, which came in at 6 percent. Currently, the figure is just a little more than the 6.01 percent noted in January, hence unlikely to meet the central bank's projection for inflation for the term ending in March, which is 5.7 percent. February's retail inflation hit a new high since June 2021, at 6.26 percent, largely driven by surging food prices.

The food group, accounting for 39% of the overall CPI basket, rose 5.85% in February. The number was 0.68% in September of last year. Food inflation is getting more generalized, even as some items, such as edible oils, remain stuck in double-digit inflation. Core inflation, excluding the more volatile food and fuel prices, rose 5.98%, marginally lower than the 6.01% in January. Non-core inflation, which jumped to 6.27% in February, has been rising rapidly, according to data from the Centre for Monitoring Indian Economy. Non-core is likely to rise further as fuel prices have increased, with crude oil prices shooting up since the outbreak of conflict between Russia and Ukraine.

In Monday’s statistics, it also emerged that the Wholesale Price Index (WPI) rose by 13.11%, thereby ending the previous three-month period’s decline in wholesale prices. Since April 2021, the Wholesale Price Index has stayed in the double digits.

Perpetual and high food inflation have presented challenges for monetary management in India. While many economists argue that central banks, such as the RBI, must only respond to changes in

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fundamental core inflation, there is mounting evidence that the dynamics of food price inflation in emerging economies might differ significantly. As a result, neglecting food inflation in monetary policy decisions may result in policy oversights. The purpose of this paper is to investigate the relevance of the food price index, often known as

inflation, in India's monetary policy management. To do so, we need to first figure out why India's food inflation is so high. There are influences on both the demand and supply sides. This paper also focuses on the role of fuel inflation and the transmission of oil price shocks to create dynamics of food inflation in India. Beyond this, we secondly analyze the role of price expectations to determine food inflation. We construct a VAR or (vector autoregression) model to describe the link between food price inflation and its determinants with their previous values to investigate the framework of food inflation and its drivers in India. It's utilized to model the combined dynamics and causal relationships between groups of macroeconomic factors.

Literature Review

- **Mitchell(2008)** argues that the processing of biofuels from grain and oilseed crops in the US and EU accounted for about two-thirds of the price escalation of these products between 2002 and 2008.
- **Krugman (2008)** observed that the rise in per capital income in the emerging markets has led to a change in the eating habits of the populace to meats, which in turn increased the demand for grains to feed the livestock.
- In the context of high food inflation in India, it has been argued that supply side constraints causing high food inflation was rooted in slow growth in agriculture sector**(Carraso and Mukhopadhyay,2012; Desi *et al.* 2011, GOI, 2012, Chado 2010.)**
- **Naveed and Yadav, (2013)** stated that with the increase in the number of poor persons due to the implementation of the inclusive growth model, there is increased demand for food, but with constant per capita supply, food prices have increased.
- **Kumar *et al.* (2010)** argued that there are various structural and situational factors that have contributed to the rising rate of food inflation in India, for example, the divergence in per capita income, the reduction in the availability of food, and subsequently the rise in demand for food.
- **Sasmal (2015)** concluded that the rise in per capita income and failure of agriculture production to keep the pace with growing demand has added fuel to the food prices.
- **Bhattacharya and Bhattacharyya (2001)** argued that a number of structural and situational factors have impacted the rising food inflation in India, including the discrepancy in per capita income, the reduction in food availability, and the resultant rise in the demand for food products.
- **Bhattacharya and Kar (2005)** applied a macroeconomic modeling technique to analyze the immediate and extended effects of increased global oil prices on the economy of the nation. It was observed that oil price shocks had a stagflationary impact in the short term, with a decline in output and an uptick in inflation; its negative effects continued on growth into the long term as well.
- **Bhanu Murthy, Das, and Bose (2012)** developed a structural macroeconomic model to analyze the influence of oil price changes on major macroeconomic variables in India. In this study, evidence has been obtained about the harmful impact of an increase in international oil prices on the GDP growth rate during the initial periods of the 12th Five-Year Plan (2012-2017) in the Indian planning cycle, along with a positive impact of this shock on inflation not only during the year but for the entire duration of the plan.
- **Bhat (2014)** studied the differential impact of oil price changes on the macroeconomic

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indicators of India in an asymmetric fashion using a multivariate VAR model on monthly time series data. The study emphasized the asymmetric impact of oil price shocks, indicating that the negative shock significantly affected macroeconomic indicators in India, whereas the positive shock had a smaller impact.

- **Holtemoller and Mallick(2016)** They followed a two-model approach to test the effect of international food prices on the general price level and domestic food prices. Using both SVAR and the New Keynesian Models (Bayesian Estimation), the study concluded that, in the presence of exogenous rainfall shocks, a large fraction of the variation in India's inflation is explained by cost-push variables and international food price shocks in 2008 and 2010.
- **Cavallo A.** analyzed the changes in the expenditure behavior of the consumers, leading to the impact on the CPI. The researcher observed that inflation caused by the COVID-19 pandemic exceeded the actual readings in the US for the headline and core CPI indices.
- **Seiler P.** Investigated the connectedness between the Covid and inflation for Switzerland.
- **Lane T.** mentioned that during this period of quarantine, the rates of inflation declined sharply because of changes in gasoline prices, travel services, and consumer spending patterns in Canada. The author emphasized that in this scenario, a rather proactive attitude of monetary policy compared to normal situations would be required.

Data and Methodology

This paper uses secondary data obtained from the Handbook of Statistics on India Economy published by Reserve Bank of India(RBI). This research also uses the Economy Survey of India 2021. Data of the Consumer Price Index(CPI) and Food Price Inflation (FPI) is obtained from the Food and Agriculture Organization of the United Nations (FAOSTAT) and International Monetary Fund (IMF) respectively. The study is based on the time series data from 1992-2021. Where the annual average of CPI and FPI is calculated on YoY(Year on Year) basis. To examine the framework of food inflation and its determinants in India, we estimate a VAR or (vector autoregression) model to explain the relationship between food price inflation and its determinants with their past values. It's utilized to model the interactions and causal relationships between a group of macroeconomic variables. Sims (1980) popularized the vector autoregressive model (VAR) in econometrics as a natural development of univariate autoregressive models. In other words, when two or more time-series interact, VAR is a forecasting methodology that can be applied. When Sims promoted vector autoregression (VAR) models as alternatives, multivariate simultaneous equations models were widely employed for macroeconomic analysis. In contrast to the simultaneous equations model, the VAR model does not need endogenous or exogenous variables. In economics, it is used to time series.

In contrast to these variables, all variables in VAR are endogenous (Elgar, 1992). Each variable in the system, as well as its own. lagged values and the lagged values of other variables, are all linear functions in VAR models. The right side of each equation in the VAR model will include the same variables if there is no restriction. In addition, in VAR models, the lagged values of dependent variables allow for accurate future forecasts (Kumar, Leona, Gaskin, 1995). There are n equations in traditional simultaneous equation models with n endogenous i.e., dependent variables, one for each endogenous variable. One or more endogenous

variables and some exogenous variables may be present in each equation. Before these equations can be estimated, we have to make sure that the problem of identification is solved, that is, whether the parameters or set of parameters can be consistently estimated. Arbitrary restrictions are commonly applied to accomplish identification by omitting some variables from an equation that may be present in other equations in the system. Sims opposed this method, claiming that if there are n

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endogenous variables, they should all be treated identically; no differentiation between endogenous and exogenous variables should be established. As a result, each equation should have the same amount of regressors. To overcome this problem, Sims invented the VAR model (Damodar Gujarati, 2001). The motivation for using the vector autoregression (VAR) model is to take into account the interrelationship between various economic variables. In this relationship, the value of one economic variable is determined simultaneously with the value of many other economic variables. So here, a VAR model is needed as a multivariate framework that recognizes the interrelationship between economic variables as well as their dynamic features. The VAR model has several advantages. To begin with, it's really straightforward. Whether the variables are endogenous or exogenous is irrelevant to the econometrician. In this context, everything is endogenous. The value of a variable can be influenced by factors other than its own lags or white noise terms when using VAR. VAR beats univariate autoregression models in this situation. Second, estimation is also very simple, in the sense that the OLS method can be used to evaluate each equation separately. Third, VAR models produce better forecasts than the significantly more difficult simultaneous equation models in the vast majority of circumstances (Mahmoud, 1984; McNees, 1986). The autoregression (AR) model may be thought of as a subset of the VAR model. As a result, the VAR model outperforms complex macroeconomic models in terms of predicting. Complex macroeconomic models can be outperformed by regression-based techniques. Finally, the VAR model has a highly rich structure, which means it may be able to capture more data characteristics. This is a strong motivation for using the VAR model.

The Granger causality is used to investigate the dynamic interaction between economic factors. In econometrics, it's a well-known idea. “Correlation does not entail causality,” is one of the first and most obvious principles introduced to any economist or econometrician. Correlation or covariance is a symmetric. In simple words, covariance of x and y or y and x both are same. Non-zero covariance can’t be used to conclude whatever nearly the presence or direction of causation between x and y. Even if our statistical study shows that the covariance could not take happened by unplanned, such a association may exist because x causes y, y causes x, one causes the other, or x and y are retorting to a third variable without any causal link between them. To put it another way, correlation does not always indicate causation in any meaningful way. Some econometric studies contain a plethora of striking correlations that are either false or useless. Clive Granger, on the other hand, coined the term "granger causality." The exact meaning of Granger causality states that previous values of x help in the prediction of y, provided that the effects of past values of y and perhaps other variables on y have already been reported for. Once they do, the x is considered to be the “Granger Cause” y. The VAR is an excellent framework for investigating Granger causality.

VAR Model

A vector autoregression (VAR) is a set of k time-series regressions, in which the regressors are lagged values of all k series. A VAR broadens the univariate autoregression to a list, or "vector," of time series variables. When the number of lags in each of the equations is the same and is equal top, the system of equations is called a VAR (p). In the case of two-time series variables, Y_t, and X_t , the VAR
(p) consists of the two equations;

$$\mathbf{Yt = \beta 10 + \beta 11 Yt\text{-}1 + \cdots + \beta 1p Yt\text{-}p + \gamma 11 Xt\text{-}1 + \cdots + \gamma 1p Xt\text{-}p + \mu 1t \ldots. (1)}$$

$$\mathbf{Xt = \beta 20 + \beta 21 Xt\text{-}1 + \cdots + \beta 2p Xt\text{-}p + \gamma 21 Yt\text{-}1 + \cdots + \gamma 2p Yt\text{-}p + \mu 2t \ldots. (2)}$$

Where the β's and the γ's are unknown coefficients and μ_{1t} and μ_{2t}, are error terms. Here μ_{it} is a white noise disturbance term with $E(\mu_{it}) = 0$, (i =1, 2), $E(\mu_{1t}\ \mu_{2t}) = 0$. Another useful facet of VAR models is the compactness with which the notation can be expressed. For example, consider the case from above where p
=1, so that each variable depends only upon the immediately previous values of Y_t and X_t, plus an

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error term. This could be written as

$Yt = \beta 10 + \beta 11Yt\text{-}1 + \gamma 11Xt\text{-}1 + \mu 1t$ …. (3) $Xt = \beta 20 + \beta 21Xt\text{-}1 + \gamma 21Yt\text{-}1 + \mu 2t$ …. (4)

A key feature of the above equations (3) and (4) is that no current variables appear on the right-hand side of any of the equations. So that there are no contemporaneous terms on the RHS of (3) or (4) – i.e., there is no term in X_t on the RHS of the equation for Y_t and no term in Y_t on the RHS of the equation for X_t. This makes it valid or logical, however not always certain, that the regressors of (3) and (4) are weakly exogenous and that, if all of the variables are stationary and ergodic, OLS can produce asymptotically desirable estimators. It is assumed that all the variables in the VAR (p) are have no unit root. Individual coefficients can be estimated and tested using OLS P-values or t statistics.

a. Granger Causality (Block Significance and Causality Tests)

With time-series variables, Granger causality is only applicable. If event A occurs before occurrence B, it is possible that A is the cause of B. To put it another way, previous events can influence current occurrences. Past events have little influence on future occurrences. Consider two variables x and y. The fundamental principle is that if past values of x may assist explain y, then a variable x Granger causes y. So, the Granger (1969) approach to the question of whether x causes y is to examine how much of the current y can be described by past y values and then to see if adding lag x values strengthens the interpretation. If x contributes to the prediction of y, or correspondingly if the coefficients on the lagged x's are statistically significant, y is said to be Granger-caused by x. Remark that in most cases, two-way causation exists: x Granger causes y, and y Granger causes x. It's worth remembering that the phrase "x Granger causes y" does not imply that y is x's consequence or outcome. In other words, it does not imply that changes in one variable induce changes in another.

Granger causality takes into consideration the order of events and the availability of information, but it does not entail causation in the traditional sense. The idea that the cause occurs before the effect, which is the basis of this definition, is used in most, but not all, causality definitions. Another method to describe granger causality is to look at it from a different perspective. Let's take a look at Y_t and Z_t once again. Using past Z_t terms, we can anticipate Y_{t+1}. First if, Z_t happens before Y_{t+1} and second, it includes information valuable in anticipating Y_{t+1}, then Z_t would be said to be the “Granger cause” Y_{t+1}. To conduct the causality test, recall the equations (3) and (4)!

$Yt = \beta 10 + \beta 11Yt\text{-}1 + \gamma 11Xt\text{-}1 + \mu 1t$ $Xt = \beta 20 + \beta 21Xt\text{-}1 + \gamma 21Yt\text{-}1 + \mu 2t$

The assumptions, as well as the implicit restrictions on the parameter matrices, are listed in the table below.

No.	Hypothesis	Implied Restriction
1	Lags of Y_t do not explain current X_t	**$\gamma 21=0$**
2	Lags of Y_t do not explain current Y_t	**$\beta 11=0$**
3	Lags of X_t do not explain current Y_t	**$\gamma 11=0$**
4	Lags of X_t do not explain current X_t	**$\beta 21=0$**

Table 2 Granger Causality Tests Source: Author’s Estimation

Because each set of restrictions contains parameters generated from a single equation, the joint hypotheses may be easily tested using the F-test framework, provided that all of the VAR variables are stationary. Causality tests are a term

that may be used to specify the tests mentioned above. Granger (1969) described this type of test, as well as a minor modification owing to Sims (1972). Simple queries such, "Do changes in x cause

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changes in y?" are addressed with causation tests. If x causes y, the lags of x should be significant in the equation for y, according to the reasoning. If this is the case, rather than the other way around, it is stated that x 'Granger-causes' y or that unidirectional causation occurs from x to y. If y causes x, on the other hand, the lags of y should be significant in the equation for x. It is claimed that there was "bi-directional causation" or "bi- directional feedback" if both sets of lags were significant. Variable x is considered to be extremely exogenous if it is proven to Granger-cause y but not the other way around in the equation for y. x and y are considered to be independent if neither pair of lags in the equation for the other variable is statistically significant. Finally, the word "causality" is misleading since Granger-causality only refers to a correlation between the present value of one variable and its previous values; it does not imply that one variable causes the movement of another.

b. Model Specification

Before estimating the VAR model, we first specify the system of the model. Here our sole motive is to highlight the relevance of the food inflation issue in the Indian Economy. To check this systematically, we first introduce all variables for the statistical framework.

No.	Variable	Name	Source
1	CPI	Consumer Price Index	RBI Data Base
2	FPI	Food Price Inflation	FAOSTAT Data
3	GFD	Gross Fiscal Deficit	RBI Data Base
4	M3	Money Supply	RBI Data Base
5	FEL	Fuel Energy Index	IMF Data Base
6	CTA	Credit To Agriculture	RBI Data Base
7	MSPp	Minimum Support Price for Paddy	RBI Data Base

For the statistical framework, we classified all variables into two models. (a) first is how the consumer price index in India, is explained by macroeconomic variables (both fiscal and monetary variables) as well as food price inflation; (b) second is how the food price inflation in India, is explained by fuel energy index, credit to agriculture and minimum support price. Here we include the FPI in model 1 to understand the role of food price inflation and also to check how FPI influences the consumer price index. The main motive of the introduction of two models is that to examine the macroeconomic framework of food price inflation, and to highlight the importance of FPI as a part of monetary policy management in India.

No.	Variable	Remark
1	CPI	Dependent Variable
2	FPI	Independent Variable
3	GFD	Independent Variable
4	M3	Independent Variable

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Table 4 Model 1 Specification

No.	Variable	Remark
1	FPI	Dependent Variable
2	FEL	Independent Variable
3	CTA	Independent Variable
4	MSPp	Independent Variable

Table 5 Model 2 Specification

Stationarity Condition and VAR Model

Stationarity is a key requirement when working with time series. The memory of non-stationary time series is wide, whereas the memory of stationary time series is less. If the probability distribution of a time series remains constant throughout time, it is called stationary. When a time series exhibits the following three properties, it is covariance stationary:

(a) displays mean reversion, fluctuating around a fixed long-run mean;
(b) has a time-invariant finite variance; and
(c) has a theoretical correlogram that reduces as the lag duration rises. In other words, a time series is said to be stationarity if it has a constant mean, variance, or covariance over time.

A key concept underlying time series processes is that of stationarity. So here we check the stationarity condition of all series. By conducting the Augmented dicky fuller (ADF) test, for both model 1 and model 2, we can check whether the time series has a unit root or not. A time series has a unit root, meaning is that series is non-stationary.

6.1 Unit Root Test for Model 1

By conducting the ADF test, we find all the variables are non-stationary or have a unit root at a level. By taking the first-order difference, we again check the stationarity condition. At first-order difference all variables are stationary. The result of the ADF test is given below in the table for both models.

Table 6 Augmented Dickey-Fuller (AFD) for Unit Root (Model 1) Source: Author's Estimation

	At Level		At 1st Difference		
Variables	t-statistics of ADF	Prob. Values	Variables	t-statistics of ADF	Prob. Values
CPI	0.7155	3.012	LCPI_d1	0.0171	-3.253
FPI	0.845	-3.414	LFPI_d1	0.0039	-2.989
M3	1.000	14.114	LM_d1	0.0001	-4.641
GFD	0.9007	0.191	LGFD_d1	0.0000	-5.678

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Results shows that by taking the first-order difference all variables become stationary. For model 1 (Table 6), the first null hypothesis is that variables have an individual root process. Here our significance level is 5%. So, P-value associated with ADF statistics are less than 0.05. So here we have enough evidence to reject the null hypothesis is that all variables have a unit root or non- stationary.

VAR Model 1-Estimation

a. Lag-order Selection Statistics

Before proceeding with the VAR model estimation, we have to find out the optimum lag order of model 1. Lag lengths in a VAR can be determined using information criteria.

Table 7 Lag Selection Criteria of VAR Model 1 Source: Author's Estimation

Lag	LL	LR	Df	P	FPE	AIC	HQIC	SBIC
0	64.0954							
1	92.3784	56.566	16	0.000	3.7e-088*	-5.79027*	-5.51982*	-4.815177-*
2	98.1881	11.619	16	0.770	6.8e-08	-4.97505	-4.89637	-3.21987
3	121.994	47.612*	16	0.000	6.8e-08	-5.59955	-4.89637	-3.06428

*Indicates lag order selected by the criterion

LR: sequential modified likelihood ratio test statistic (each test at 5% level) FPE: Final prediction error
AIC: Akaike Information criterion SC: Schwarz Information criterion
HQ: Hanna-Quinn Information criterion

Criteria embody two factors; the first term is a function of the residual sum of squares, and the second is the loss of degrees of freedom from adding extra parameters. There are three criteria Akaike's Information Criterion (AIC), and Hannan-Quinn Information Criterion (HQIC), Schwarz's Bayesian Information Criterion (SBIC). Here the objective is to choose the order of lag that minimizes the value of the information criteria. According to lag-selection criteria, we take one as a lag-order of VAR model 1.

b. Model Results

The given below table 8 shows the results of the VAR model 1 estimation.

Table 8 VAR Model 1 Results Source: Author's Estimation

Lag	Y X	LCPI_d1	LFPI_d1	LGFD_d1	LM3_d1
(L1)	LCPI_d1	-0.1687862	0.0177755	0.1830614*	0.468964*
(L1)	LFPI_d1	-0.7094605	0.135705	0.4389577*	7.824448*
(L1)	LGFD_d1	1.018723*	0.0039378	0.638911*	-0.8921364
(L1)	LM3_d1	-0.026444	1.198878	-0.0092056	1.198878*
	R-sq	0.9688	0.5413	0.9634	0.997
	chi2	869.0702	8.87865	736.9551	95288.74
	P>chi2	0.0000	0.3526	0.0000	0.0000

7.2 **VAR Diagnostics and Tests**

To assess the validity of our VAR model 1, we test for stability and autocorrelation of the residuals and normally distributed disturbances.

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7.2.1 Stability Conditions of VAR model 1 Estimates

7.2.2 **Table 9 Stability Conditions of VAR Model 1 Source: Author's Estimation**

Eigenvalue stability condition

Eigenvalue	Modulus
.9677798	.96778
.6398259 + .1343981i	.653789
.6398259 - .1343981i	.653789
-.01366326 + .5869956i	.587155
-.01366326 - .5869956i	.587155
-.4259881	.425988
.00532338 + .2932016i	.29325
.00532338 - .2932016i	.29325

All the eigenvalues lie inside the unit circle.
VAR satisfies stability condition.

7.2.3 LM test for Residual Autocorrelation of Model 1

Table 10 Lagrange-Multiplier Test for Model 1 Source: Author's Estimation

Here null hypothesis is that no autocorrelation at lag order. Here our lag order is one and the p-value associated with chi-square is 0.6339 which is greater than

Lagrange-multiplier test

lag	chi2	df	Prob > chi2
1	13.5299	16	0.63369
2	15.8943	16	0.46037

H0: no autocorrelation at lag order

0.05. Thus, we can have enough evidence to support or accept the null hypothesis is that there is no autocorrelation at lag order one.

7.2.4 **Test for Normally Distributed Disturbances of Model 1**

Table 11 Normality Test for Model 1 Source: Author's Estimation

Skewness/Kurtosis tests for Normality

Variable	Obs	Pr(Skewness)	Pr(Kurtosis)	joint adj chi2(2)	joint Prob>chi2
myResiduals	27	0.2390	0.3715	2.40	0.3013

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In this test null hypothesis is that disturbances are normally distributed. Here results show that overall p-value (Kurtosis Test) associated with chi-square is greater than,0.05, which is significant. Got enough evidence to accept the null hypothesis.

7.4 Granger Causality Tests

Table 12 Granger causality Wald Tests for Model 1 Source: Author's Estimation

Equation	Excluded	Chi2	Df	Prob>chi2
LCPI_d1 LCPI_d1	LGFD_d1 LFPI_d1	8.0861	2	0.018
LCPI_d1	LM3_d1	4.6129	2	0.100
LCPI_d1	ALL	16.204	2	0.020
		31.874	6	0.003
LGFD_d1 LGFD_d1	LCPI_d1 LFPI_d1	8.5779	2	0.014
LGFD_d1 LGFD_d1	LM3_d1 ALL	1.4024	2	0.496
		0.7267	2	0.695
		21.184	6	0.002
LFPI_d1 LFPI_d1	LCPI_d1 LGFD_d1	0.21853	2	0.896
LFPI_d1 LFPI_d1	LM3_d1 ALL	0.79237	2	0.673
		2.5735	2	0.276
		3.6898	6	0.719
LM3_d1 LM3_d1	LCPI_d1 LGFD_d1	1.5965	2	0.450
LM3_d1	LFPI_d1	7.1119	2	0.029
LM3_d1	ALL	1.0519	2	0.591
		15.699	6	0.015

Here Granger causality test shows the overall significant result for the primary equation of consumer price index as the dependent variable. According to the test current value of CPI significantly (p-value is less than 0.05) explained by the past values of M3. In other words, the lags of the money supply are significant in the equation for CPI. So, it can say that M3 'Granger-causes' CPI or that there exists unidirectional causality from M3 to CPI. Again, for the primary equation of consumer price index as the dependent variable, the overall p-value is 0.003 which is less than 0.05. So, the primary equation, all the past values (here at lag order 1) of independent variables (food price inflation, gross fiscal deficit, money

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supply) jointly explained the current value of the consumer price index. In other words, all variables (food price inflation, gross fiscal deficit, money supply) jointly 'Granger-causes' CPI.

VAR Model 2-Estimation

c. Unit Root Test for Model 2

Table 13 Model 2 Unit Root Test Source: Author's Estimation

	At Level		At 1st Difference		
Variables	t-statistics of ADF	Prob. Value	Variables	t-statistics of ADF	Prob. Values
FPI	-3.414	0.0105	LFPI_d1	-3.712	0.0039
CTA	-1.622	0.9865	LCTA_d1	-5.975	0.0000
FEL	-1.622	0.4718	LFEL_d1	-4.867	0.0000
MSPp	0.9986	0.556	LMSPp_d1	-4.090	0.0010

Here the main aim is to check the unit root test hypothesis. The null hypothesis is that variables have an individual unit root process. In this all variables (FPI, CTA, FEL, MSPp) having p-value less than 0.05. Which states that all variables in Model 2, don't have Individual unit root process. We are rejecting the null hypothesis is that all variables have a unit root or non-stationary.

d. Lag-Order Selection Statistics

Table 14 Lag Selection Criteria of VAR Model 2 Source: Author's Estimation

Lag	LL	LR	Df	P	FPE	AIC	HQIC	SBIC
0	-53.4228				0.00827*	4.25354*	4.31063*	4.44552*
1	-40.4243	25.997	16	0.054	0.001051	4.47588	4.7613	5.43576
2	-25.9767	28.895*	16	0.025	0.001288	4.59087	5.10463	6.31865

*Indicates lag order selected by the criterion

LR: sequential modified likelihood ratio test statistic (each test at 5% level) FPE: Final prediction error
AIC: Akaike Information criterion
SC: Schwarz Information criterion
HQ: Hanna-Quinn Information criterion

8.2 **Model Results**

The given table 15 shows the results of the VAR Model 2 estimation

Table 15 VAR Model 2 Estimation

Lag	Y X	LFPI_d1	LCTA_d1	LFEL_d1	LMSPp_d1
(L1)	LFPI_d1	-0.6892902	-0.451821	1.211421*	-0.428772
(L2)	LFPI_d1	-0.1161986	0.4496247*	2.047774*	-0.435716

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(L1)	LCTA_d1	0.0679867	-0.215893	0.132665*	-0.008685
(L2)	LCTA_d1	0.0193353	-0.0138565	-0.816557	-1.290962
(L1)	LFEL_d1	0.036056	0.1646427*	0.033076	-0.0434779
(L2)	LFEL_d1	0.1187695*	0.296066*	-0.5352535	-0.9070991
(L1)	LMSPp_d1	0.0273766	0.024711	0.1059164*	0.4547982*
(L2)	LMSPp_d1	0.0170227	-0.0050143	-0.0927068	-0.2765374
	R-sq	0.5551	0.2651	0.5013	0.3312
	chi2	33.69339	9.73998	27.13546	13.37126
	P>chi2	0.0001	0.2838	0.0007	0.0997

Source: Author's Estimation Note: *Significant at 5% Level.

8.3 VAR Diagnostics and Tests

To assess the validity of our VAR model 2, we test for stability and autocorrelation of the residuals and normally distributed disturbances.

8.3.1 Stability Conditions of VAR Model 2 Estimates

Table 16 Stability Conditions of VAR Model 2

Eigenvalue stability condition

Eigenvalue	Modulus
.1903104 + .7615288i	.784949
.1903104 - .7615288i	.784949
.6993527	.699353
-.4087004 + .4435889i	.603164
-.4087004 - .4435889i	.603164
.1919952 + .5353973i	.568781
.1919952 - .5353973i	.568781
-.5643063	.564306

All the eigenvalues lie inside the unit circle.
VAR satisfies stability condition.

8.3.2. LM Test for Residual Autocorrelation of Model 2

Table 17 Lagrange-Multiplier Test for Model 2

Lagrange-multiplier test

lag	chi2	df	Prob > chi2
1	14.1058	16	0.59083
2	8.8774	16	0.91837

H0: no autocorrelation at lag order

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Here the p-value is greater than 0.05. Thus, we have enough evidence to support the null hypothesis that there is no autocorrelation at lag order 1.

8.3.3. Test for Normally Distributed Disturbances of Model 2

Table 18 Normality Test for Model 2 Source: Author's Estimation

Skewness/Kurtosis tests for Normality

Variable	Obs	Pr(Skewness)	Pr(Kurtosis)	joint adj chi2(2)	joint Prob>chi2
myResiduals	27	0.9346	0.9568	0.01	0.9952

In this test null hypothesis is that disturbances are normally distributed. Here results show that p-value associated with chi-square is greater than 0.05, which is significant. We have enough evidence to accept the null hypothesis is that disturbances are normally distributed.

8.4.4. Granger Causality Tests

Equation	Excluded	Chi2	Df	Prob>chi2
LFPI_d1 LFPI_d1 LFPI_d1 LFPI_d1	LCTA_d1 LFEL_d1	0.09598	2	0.018*
	LMSP_d1	6.961	2	0.100
	ALL	4.6537	2	0.020*
		19.522	6	0.003*
LCTA_d1 LCTA_d1 LCTA_d1 LCTA_d1	LFPI_d1 LFEL_d1	1.67	2	0.434
	LMSP_d1 ALL	5.8665	2	0.053*
		0.14548	2	0.930
		9.7515	6	0.136
LFEL_d1 LFEL_d1 LFEL_d1 LFEL_d1	LFPI_d1 LCTA_d1	0.75837	2	0.684
	LMSP_d1 ALL	5.6614	2	0.059*
		2.6583	2	0.265
		9.528	6	0.146

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LMSP_d1	LMSP_d1	LFPI_d1	LCTA_d1	11.8	2	0.003*
LMSP_d1		LFEL_d1		1.0566	2	0.590
LMSP_d1		ALL		9.822	2	0.007*
				17.481	6	0.008*

Table 19 Granger Causality Wald Test for Model 2 Source: Author's Estimation

Here Granger Causality test shows the overall significant result for the primary equation of food price inflation as the dependent variable. According to the test current value of FPI significantly (p-value is less than 0.05) is explained by the past values of the credit to agriculture and MSP only. In other words, the lags of CTA and MSP are significant in the equation for FPI. So, it can be said that CTA and MSP 'Granger-causes' FPI or that there exists unidirectional causality from CTA and MSP to FPI. For the primary equation of food price inflation as the dependent variable, the overall p-value is 0.003 which is less than 0.005. Here we got another enough evidence to accept the alternative hypothesis that CTA & MSP 'Grange-Causes' FPI. So, the primary equation, all the past values (here at lag order 2) of independent variables (Fuel Energy Index, Credit to Agriculture, and Minimum Support Prices for Paddy) jointly explained the current value of food price inflation. In other words, all variables (Fuel Energy Index, Credit to Agriculture, and Minimum Support Prices for Paddy) jointly 'Granger-causes' FPI. In equation 2 where FEL is a dependent variable, CTA 'Granger-causes' FEL. Here we have enough evidence to reject the null hypothesis is that CTA does not 'Granger-causes' FEL. In equation 4, where the minimum support price for paddy is the dependent variable, we have enough evidence to accept the alternative hypothesis is that FEL 'Granger-causes' MSPp but here point to be noted that the overall p-value is 0.008 which is less than 0.05. So we have enough evidence to accept the alternative hypothesis that food price inflation, fuel energy index, and credit to agriculture jointly 'Granger-causes' MSPp.

Conclusion and Policy Implications.

The results from the VAR model have shown the role of economic factors on inflation. The first model shows that the consumer price index is explained by a joint framework of fiscal and monetary variables in India, significantly. According to Granger causality tests in model 1, the current value of CPI is significantly explained by the past values of M3. In other words, the lags of the money supply are significant in the equation for CPI. So it can be said that there exists unidirectional causality from M3 to CPI. Again for the primary equation of consumer price index as the dependent variable, all the past values of independent variables (food price inflation, gross fiscal deficit, money supply) jointly explained the current value of the consumer price index. In other words, all variables (food price inflation, gross fiscal deficit, money supply) jointly 'Granger-causes' CPI. In model 2, granger causality tests show that the current value of FPI is significantly explained by the past values of the fuel energy index only. In other words, FEL 'Granger-causes' FPI, very significantly. Again it is a very important conclusion that all the past values of independent variables; fuel energy index, credit to agriculture, and minimum support price for paddy jointly explained the current value of food price inflation, significantly in India. In other words, all variables (fuel energy index, credit to agriculture, and minimum support price for paddy) jointly 'Granger-causes' FPI in India.

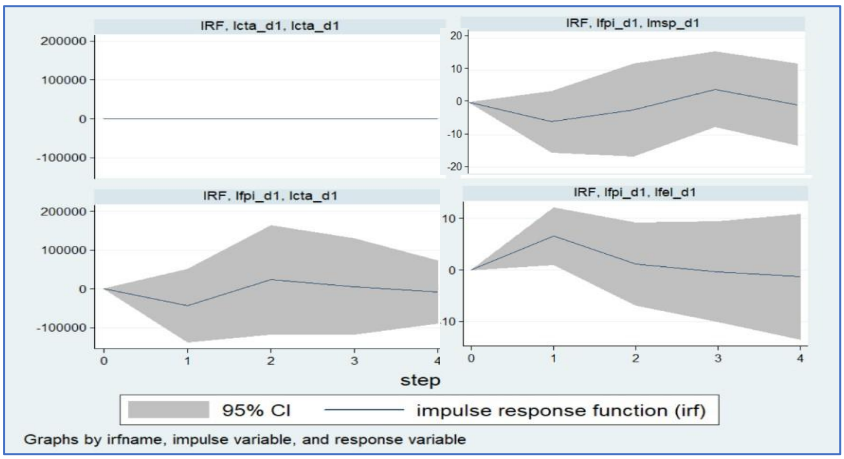
9.1.1 Evaluating the Result: Impulse Responses

The change in the present and predicted future value of a random variable conditional on the realizations of uncertainty at some point in time is known as an impulse response function. The impulse responses show how responsive the dependent variables are to shocks to each of the variables in the VAR. So far, a unit shock has been delivered to each variable from each equation, and the consequences on the VAR system have been observed over time.

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In the below figure, the horizontal axis for each graph is in the units of time that our VAR is estimated in, in this case, years; hence, the impulse–response graph shows the effect of a shock over a 20-years period. The vertical axis is in units of the variables in the VAR; in this case, everything is measured in percentage points, so the vertical units in all panels are percentage point changes. Let's focus on the result. Here we are examining how LnFPI_d1 responded to impulses in its own innovations, innovations to LnCTA_d1, innovations to LnFEL_d1, and innovations to LnMSPp_d1. The upper-left graph shows the IRF of innovation in LnCTA_d1 on LnFPI_d1.

Figure 20 Impulse Response Functions of FPI Source: Author's Estimation



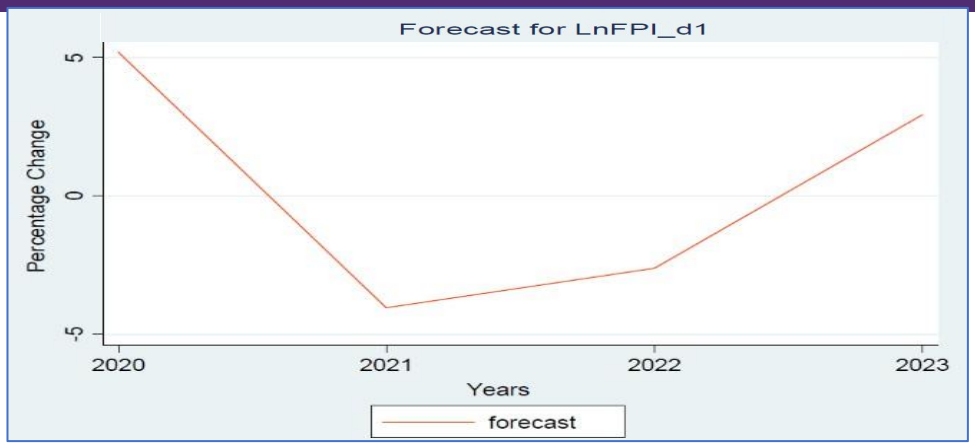
In other words, it shows the response of FPI to one standard deviation shock to CTA. It implies that a positive shock to CTA causes an increase in FPI, followed by a decrease, followed by an increase, and so on (creating a cyclical pattern) until the effect dies out after roughly 10 Years. The upper-right graph shows the
IRF of innovation in LnFEL_d1 on LnFPI_d1. It indicates that a positive shock to FEL causes an increase in FPI, followed by an increase, followed by a decrease, and so on until the effect dies out after roughly 12 Years. Finally, the lower-left graph shows the IRF of innovation in LnMSPp_d1 on LnFPI_d1. It shows that a positive shock to MSPp causes an increase in FPI, followed by a cyclical pattern until the effect dies out after roughly 15 Years.

9.2 Forecasting of Food Price Inflation in India

We must apply additional identification assumptions in order to detect structural shocks and their dynamic consequences on food price inflation. However, without making any additional assumptions, a simple VAR system can be utilised for two fundamental econometric tasks. The first strategy is to use Granger causality analysis to infer information about the direction or directions of causality between FPI and its dependent variables, and the second method is to develop forecasts for FPI and its dependent variables.

Figure 21 Three years ahead forecasting for FPI Source: Author's Estimation

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References

1. Agrawal, P., & Kumarasamy, D. (2012). *Food Price Inflation in India: Causes and Cures*.
2. Anand, R., Ding, D., Tulin, V., Cashin, P., Chalk, N., Garcia-Saltos, R., Ghate, C., Papi, L., Portillo, R., & Richardson, T. (2013). *Food Inflation in India: The Role for Monetary Policy IMF Working Paper Asia and Pacific Department*.
3. Anand, R., Kumar, N., Tulin, V., Ball, L., Cashin, P., Ghate, C., Lipsa, G., Melina, G., & Papi, L. (2016). *WP/16/2 Understanding India's Food Inflation: The Role of Demand and Supply Factors IMF Working Paper Asia and Pacific Department*.
4. Ardhana, M., & Prabhash, M. (2020). FOOD INFLATION AND ITS IMPACT ON THE URBAN POOR IN INDIA ABSTRACT. *EPRA Trust*.
5. https://doi.org/10.36713/epra2012
6. Bhat, J. A., ganaie, A. A., & Sharma, N. K. (2018). Macroeconomic Response to Oil and Food Price Shocks: A Structural VAR Approach to the Indian Economy. *International Economic Journal*, *32*(1), 66–90. https://doi.org/10.1080/10168737.2018.1446038
7. Bhattacharya, R. (2016). *How does Supply Chain Distortion affect Food Inflation in India?* http://www.nipfp.org.in/publications/working-papers/1762/ Bhattacharya, R., Gupta, A. Sen, & Sen Gupta, A. (2015). *Food Inflation in India: Causes and Consequences*. www.nipfp.org.in
8. Bhattacharya, R., Jain, R., & Singh, A. (2019). Measuring the contribution of mark-up shock in food inflation in India. *IIMB Management Review*, *31*(2), 167–
9. 181. https://doi.org/10.1016/j.iimb.2019.03.015
10. Bhattacharya, R., & Sen Gupta, A. (2018). Drivers and impact of food inflation in India. *Macroeconomics and Finance in Emerging Market Economies*, *11*(2), 146–168. https://doi.org/10.1080/17520843.2017.1351461
11. *Food and Nutrition Security Analysis, India, 2019*. (2019).
12. Gopakumar, K. U., & Pandit, V. (2017). Food inflation in India: protein products.
13. *Indian Economic Review*, *52*(1–2), 157–179. https://doi.org/10.1007/s41775-
14. 017-0006-7
15. Goyal, A., & Parab, P. (2021). What influences aggregate inflation expectations of households in India?
16. *Journal of Asian Economics*, *72*. https://doi.org/10.1016/j.asieco.2020.101260 Guillermo Gómez, J. P. (2008). *Emerging Asia and International Food Inflation Emerging Asia and International Food Inflation* (Issue 512).
17. Hoang, T. T., & van Anh Nguyen, T. (2020). The impact of macroeconomic factors on the inflation in Vietnam. *Management Science Letters*, *10*(2), 333–342. https://doi.org/10.5267/j.msl.2019.8.037
18. Huria, S., & Pathania, K. (2018). Dynamics of Food Inflation: Assessing the Role of Intermediaries. *Global Business Review*, *19*(5), 1363–1378. https://doi.org/10.1177/0972150918788763
19. *Indian Economic Survey, VOLUME-2*. (2020).

ISSN Print: 2790-6590 | ISSN Online : 2790-6582 Open Access

20. Malhotra, A., & Maloo, M. (n.d.). *Understanding food inflation in India: A Machine Learning approach*. https://ssrn.com/abstract=2908354
21. Mishra, A. (2020). Tracking the Transmission Channels of Fiscal Deficit and Food Inflation Linkages: A Structural VAR Approach. *Indian Journal of Economics and Development*, 165–172. https://doi.org/10.35716/ijed/19129 Monetary Policy Report. (2021).In *Reserve Bank of India*. https://rbidocs.rbi.org.in/rdocs/Publications/PDFs/MPRA202113A99DAD9534 4334BF6145CCBB26A744.PDF
22. Monfared, S. S., & Akın, F. (2017). THE RELATIONSHIP BETWEEN EXCHANGE RATES AND INFLATION: THE CASE OF IRAN. *European*
23. *JournalofSustainableDevelopment*,*6*(4). https://doi.org/10.14207/ejsd.2017.v6n4p329
24. Mukherjee, P., & Coondoo, D. (2019). The Indian Inflation 2006–2016: An Econometric Investigation. *South Asia Economic Journal*, *20*(1), 46–69. https://doi.org/10.1177/1391561418822205
25. Rizvi, S. A. R., & Sahminan, S. (2021). Commodity price and inflation dynamics: Evidence from BRICS. *Buletin Ekonomi Moneter Dan Perbankan*, *23*(4), 485–
26. 500. https://doi.org/10.21098/BEMP.V23I4.1418
27. Sasmal, J. (2015). Food price inflation in India: The growing economy with sluggish agriculture. *Journal of Economics, Finance and Administrative Science*, *20*(38), 30–40. https://doi.org/10.1016/j.jefas.2015.01.005
28. Sekhar, C. S. C., Roy, D., & Bhatt, Y. (2018). Food inflation and volatility in India: trends and
29. Anand, R., Kumar, N., & Tulin, V. (2016). Understanding India's Food Inflation: The Role of Demand and Supply Factors. *IMF Working Papers*, *16*(2), 1. https://doi.org/10.5089/9781513581347.001
30. Bandara, J. S. (2013). What is Driving India's Food Inflation? A Survey of Recent Evidence. *South Asia Economic Journal*, *14*(1), 127–156. https://doi.org/10.1177/1391561413477944
31. Chand, R. (2010). Understanding the nature and causes of food inflation.
32. *Economic and Political Weekly*, *45*(9), 10–13.
33. Anand, R., Kumar, N., & Tulin, V. (2016). Understanding India's Food Inflation: The Role of Demand and Supply Factors. *IMF Working Papers*, *16*(2), 1. https://doi.org/10.5089/9781513581347.001
34. Bandara, J. S. (2013). What is Driving India's Food Inflation? A Survey of Recent Evidence. *South Asia Economic Journal*, *14*(1), 127–156. https://doi.org/10.1177/1391561413477944
35. Chand, R. (2010). Understanding the nature and causes of food inflation.
36. *Economic and Political Weekly*, *45*(9), 10–13.
37. Ebrahimy E, Igan D, Peria M. The impact of Covid-19 on inflation: Potential drivers and dynamics. *IMF Special Notes Series on Covid-19. September 10, 2020:1-14.*