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Price Dynamics and Weather Anomalies in Agricultural Supply Chains

Atanu Ghoshray, Madhusudan Ghosh, and Sunghun Lim

In developing countries, certain specialty crops, highly consumed for their culture, often face increased vulnerability to price fluctuations along supply chains due to natural disasters and climate crises. Onions in India are a prime example. Leveraging monthly-level price data along the onion supply chain from March 2010 to April 2022, this study proposes a VAR-X model that explores the price dynamics among onion arrivals, retail and wholesale prices, alongside rainfall anomalies across four major cities in India. Our core finding reveals that rainfall anomalies have a significant yet contrasting effect on prices and arrivals along the onion supply chain.

Key words: VAR-X, India, Onion Prices, Price Transmission

Introduction

Countries exhibit remarkable variations in their consumption patterns, particularly con- cerning crops beyond their staple food sources. The distinct propensity of each nation towards consuming specific crops stems from a multitude of cultural and historical factors (Saberi, 2010; Mousavi and Bathaie, 2011; Benn, 2015; Martínez, Fuentes, and Bazile, 2015). For instance, China's elevated tea consumption finds its roots in the age-old practice of the revered tea ceremony. In Iran, the widespread consumption of saffron, among the world's most valuable spices, is deeply embedded in the rich cultural heritage of Persian cuisine. Across the Andean region of South America, quinoa has been a staple for millennia, holding profound dietary significance within indigenous communities like the Incas. The consumption preferences for specialty crops in each country are sometimes thrust into the forefront as major issues in agricultural policies. Particularly, unlike well-established policies supporting specialty crops and price protection in developed nations, the sharp decline in production volume or the volatility in prices due to external shocks like the weather often sparks political instability in developing countries (Wischnath and Buhaug, 2014; Patel and McMichael, 2014; Demarest, 2015; Soffiantini, 2020).

Weather anomalies are known to significantly impact the supply chain. For example, Bertrand, Brusset, and Fortin (2015) propose a new method to isolate the contribution of unseasonal temperatures from sales performance. They fit a linear relationship between temperature and sales anomalies using a regression and construct the historical distribution to determine sales-at-risk due to weather anomalies. Sarkar, Wahab, and Fang (2023) analyses the supply chain performance under weather risk. By constructing weather derivatives (e.g., options, futures, or a combination of both to minimize financial risk due to weather anomalies) to improve the performance along

Atanu Ghoshray is a professor in the Economics Group at Newcastle University Business School, Newcastle University, Newcastle-upon-Tyne, UK. Madhusudan Ghosh is a former professor in the Department of Economics & Politics at Visva-Bharati University, Santiniketan, India. Sunghun Lim (corresponding author, slim@agcenter.lsu.edu) is an assistant professor in the Department of Agricultural Economics and Agribusiness at Louisiana State University.
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the supply chain when dealing with weather-sensitive products. In a recent study, Lau, Cai, and Gozgor (2023) employ vector autoregression and impulse response analysis to examine the linkages between weather risks and international agricultural and resource prices. The study finds a linkage via demand and supply indicating that weather risks contribute to an upward pressure on agricultural prices.

In India, the onion market is a case in point. Most of the onion produced in India is domestically consumed and only a small fraction of this production is exported. Imports are almost negligible, showing that in terms of domestic consumption of onions, India is self-sufficient.[1] As an agricultural commodity of immense importance to the general population, given its culinary importance, this crop is vulnerable to weather shocks, especially with the lack of poor storage conditions. A notable incident occured back in late December 2010 where a sharp surge in onion prices was observed nationwide due to a poor harvest, leading to reduced supply. Anomalies in November's rainfall adversely impacted onion production, depleting existing stocks in storage and resulting in a lack of fresh arrivals to meet the escalating demand. This scarcity caused a staggering 135% increase in retail prices (Varma, 2010). The erratic fluctuations in onion prices frequently result in political protests and social unrest within Indian society. When prices rise, political parties in opposition take to the streets to stage mass protests, and when prices slump, disgruntled producers have dumped their produce on the streets (Matthan, 2022). Since 2011, there have been numerous instances of sharp increases in onion prices, resulting in a total of eleven protests by both producers and consumers (Rutledge, 2020). These recurring episodes of unrest prompted government intervention to stabilize the unpredictable price movements. Therefore, understanding how extreme weather events affect the price and volatility of onions in the onion supply chain is important for Indian consumers, producers, and society at large.

To deepen our comprehension, this paper aims to develop a model examining the interconnectedness between onion arrivals, retail and wholesale prices, taking into account the exogenous variable of rainfall anomalies. We examine the impact of rainfall anomalies on arrivals, wholesale and retail prices of onions along the supply chain for four major Indian cities: Delhi, Mumbai, Kolkata and Chennai over the period March 2010 to April 2022. We then compare these findings with the counterfactual where there is normal rainfall. Specifically, we employ the vector autoregressive model (VAR) with exogenous variables (X) (hereafter VAR-X model) to analyze the dynamic interaction among retail and wholesale prices as well as market arrivals of onions (treated as endogenous variables), alongside rainfall anomalies (considered as an exogenous variable).

We find that rainfall anomalies have a significant yet contrasting effect on prices across the onion supply chain: in particular, rainfall anomalies have significant positive effects on onion prices while yielding negative effects on arrivals. Further, we examine the price transmission dynamics between retail and wholesale prices alongside onion arrivals. A shock to arrivals of onions has an initial negative impact on both retail and wholesale prices for four cities. Meanwhile, our analysis reveals that wholesale prices in all cities tend not to react to retail price shocks. In contrast, retail prices demonstrate a significant response to wholesale price shocks.

Our proposed model can assist policymakers in making informed decisions regarding intervention measures, as it allows us to quantify the impact of arrivals and rainfall on onion prices. A noteworthy observation is the practice of middlemen maintaining inventories to mitigate price fluctuations in response to temporary shifts in demand and supply, as discussed in prior research (e.g., Maccini (1978) and Amihud and Mendelson (1983)). In the context of India's onion markets, while storage facilities are basic, changes in onion arrivals in the market can affect short-term price fluctuations. Therefore, our study enriches the understanding of the Indian onion market by quantifying the effects of arrivals on both wholesale and retail prices.

[1] For details, see Table A.1 in the Appendix.

Related Literature Weather conditions play a significant role in driving price fluctuations within the onion market. Research suggests a strong correlation between climate change-induced rainfall variability in India and its adverse effects on onion production and subsequent price dynamics (Meshram, Singh, and Meshram, 2017; Praveen et al., 2020). Given that onions are a staple ingredient in almost every Indian meal, any sharp increase in onion prices resonates with the government and its constituents (Parkin and Terazono, 2019). Recent years have witnessed anomalies in India's rainfall patterns and delayed monsoons, prompting the India Meteorological Department to recalibrate its normal rainfall baseline in response to the challenges posed by climate change (Shrikanth, 2019). Current research indicates an anticipated increase in rainfall anomalies due to climate change throughout the 21st century (Asharaf and Ahrens, 2015; Varghese et al., 2020), including a projected growth in inter-annual variability (Kitoh et al., 1997). Consequently, the disruptive and unpredictable rainfall patterns resulting from anthropogenic climate change in recent decades have significantly impacted onion production, leading to price fluctuations (Rutledge, 2020).

In a market economy, prices serve as a crucial mechanism for efficiently coordinating a multitude of consumers and producers, each pursuing self-interest and operating with information limited to their own preferences, technology, and constraints. Agricultural prices, in particular, often exhibit uncertainty and unpredictability in their temporal trajectories, making it challenging to discern whether external shocks will have lasting impacts. This inherent characteristic of agricultural prices poses risks for both farmers, who may adjust their production and input investments in response (Sckokai and Moro, 2009), and lower-income consumers, who allocate a significant portion of their income to food expenditures (Headey and Fan, 2008).

Nevertheless, empirical research has explored the connection between rainfall anomalies and agricultural prices. Prices are indirectly influenced by rainfall deviations through their impact on crop yields and production volumes. D'Agostino and Schlenker (2016) have concluded that climate change, leading to higher temperatures, is likely to reduce yields. Long-term temperature increases can alter the suitability of various regions for agricultural production (Kurukulasuriya and Mendelsohn, 2008). Numerous studies have documented the influence of climate change and erratic weather on yields, prices, and associated risks (e.g., Tack and Ubilava (2015); Urban, Sheffield, and Lobell (2015); Ubilava (2018); Chavas et al. (2019); Connor and Katchova (2020); Perry, Yu, and Tack (2020); Wang, Rejesus, and Aglasan (2021)). These studies have also explored the impact of crop insurance participation on the relationship between warming temperatures and yield risk, but their focus has primarily been on the United States or other OECD countries. There appears to be a scarcity of empirical research on the effects of rainfall anomalies on agricultural production in developing or emerging countries, possibly due to data limitations. In this study we address this gap by assembling data, including wholesale and retail prices along with available supplies of onions. Given the increasing weather chaos caused by climate change, understanding the link between retail and wholesale prices, as well as available supplies, is critical for comprehending interregional onion flows.

Among the limited studies investigating the impact of climate change on agriculture in India, Taraz (2018) suggests that adaptation measures are fairly effective against moderate heat levels but much less so against extreme heat. This underscores the importance of development policies that prioritize climate change-related risk mitigation. Goyal (2010) emphasizes the role of information provision in shaping the efficiency of rural markets in India. Additionally, direct interactions between producers and processors can prove beneficial in the context of agricultural marketing in India, as demonstrated by the analysis of changes in the procurement strategy of a private soybean buyer in Madhya Pradesh, which has ripple effects on prices across agricultural *mandis* in the state (Goyal, 2010). More recent research by Letta, Montalbano, and Pierre (2022) highlights the quick adaptation of traders in India to rainfall anomalies, as they anticipate the impact on future supply and make corresponding adjustments to pricing and supply decisions.

Section outlines the dataset and its description. In Section , the empirical strategy employed is detailed. Section presents the findings derived from our empirical analysis. Section carries out robustness checks. Finally, Section encapsulates the concluding remarks drawn from this study.

Data and Data Description

The data used in this study comprises wholesale and retail prices, measured in Rupees per kilogram, sourced from the Department of Consumer Affairs of India. Information regarding onion arrival volumes, measured in metric tonnes, was obtained from the National Horticulture Board, a branch of the Government of India[2]. Across different regions of India, we selected four major cities: Delhi, Kolkata, Mumbai, and Chennai, representing the north, east, west, and south regions, respectively. We choose the four cities as they are not just among the most populous cities in India, but they are also geographically most dispersed: Delhi in the north, Mumbai in the west, Kolkata in the east and Chennai in the south. Bangalore is the only city we do not choose, as it would not depict the geographical dispersion, being situated between Mumbai and Chennai.

For our analysis of rainfall deviation, we calculated the difference between the actual rainfall in selected Indian states and the 'normal' amount of rainfall as determined by the India Meteorological Department (IMD). Specifically, we computed the average rainfall in the major onion-producing states of India, including Maharashtra, Madhya Pradesh, Karnataka, Gujarat, Bihar, and Rajasthan, and then subtracted the corresponding normal rainfall values as provided by the IMD. The source of all rainfall data is the IMD.

All data used in this study are reported at a monthly frequency and cover the period from March 2010 to April 2022. Except for the rainfall deviation data, which may include negative values, we conducted our subsequent analyses on the logarithmically transformed data. To visually represent these data series in logarithms, Figure 1 displays separate panels for each of the four cities (Delhi, Mumbai, Kolkata, and Chennai), illustrating the trends in wholesale and retail prices over the study period.

The wholesale and retail price data for various cities reveal a notable pattern characterized by extended periods of relatively stable prices, occasionally interrupted by price spikes. These spikes may be attributed to factors such as stock shortages resulting from inadequate storage facilities or irregularities in rainfall that impact the overall supply. It is worth noting that the wholesale and retail price series exhibit a discernible co-movement over time, with retail prices consistently maintaining a markup over wholesale prices, as one would expect.

Importantly, these occasional price spikes do not appear to be driven solely by seasonal variations. Onions are cultivated multiple times a year, during the Kharif, late Kharif, and Rabi seasons, with harvests occurring in October to December, January to March, and April to May, respectively. In the case of purely seasonal effects, one would anticipate price increases each month between harvests to account for storage costs. However, due to the multiple harvests throughout the year, coupled with uncertainties in both demand and supply, the observed price spikes do not adhere to the regular temporal intervals. Instead, these spikes occur at more extended intervals, likely influenced by supply uncertainties and the irregularities in rainfall patterns.[3]

Onion production experiences fluctuations primarily driven by weather conditions. Deviations from the 'normal' levels of expected rainfall play a significant role in influencing the variability in onion production, which, in turn, impacts the fluctuation in onion prices. Moreover, the inadequacy and rudimentary nature of storage facilities exacerbate these challenges. These factors collectively

[2] Data was sourced from the National Horticultural Board's website: http://www.nhb.gov.in/OnlineClient/MonthwiseAnnualPriceandArrivalReport.aspx.

[3] We consider the case where there may be nonstationary volatility in the prices, given the spikes. We make use of the variance plot due to Cavaliere and Taylor (2007). The results show that the variance is reasonably close to constant variance (see Figure A.1 in the Appendix); and therefore, non-stationary volatility is not an issue.

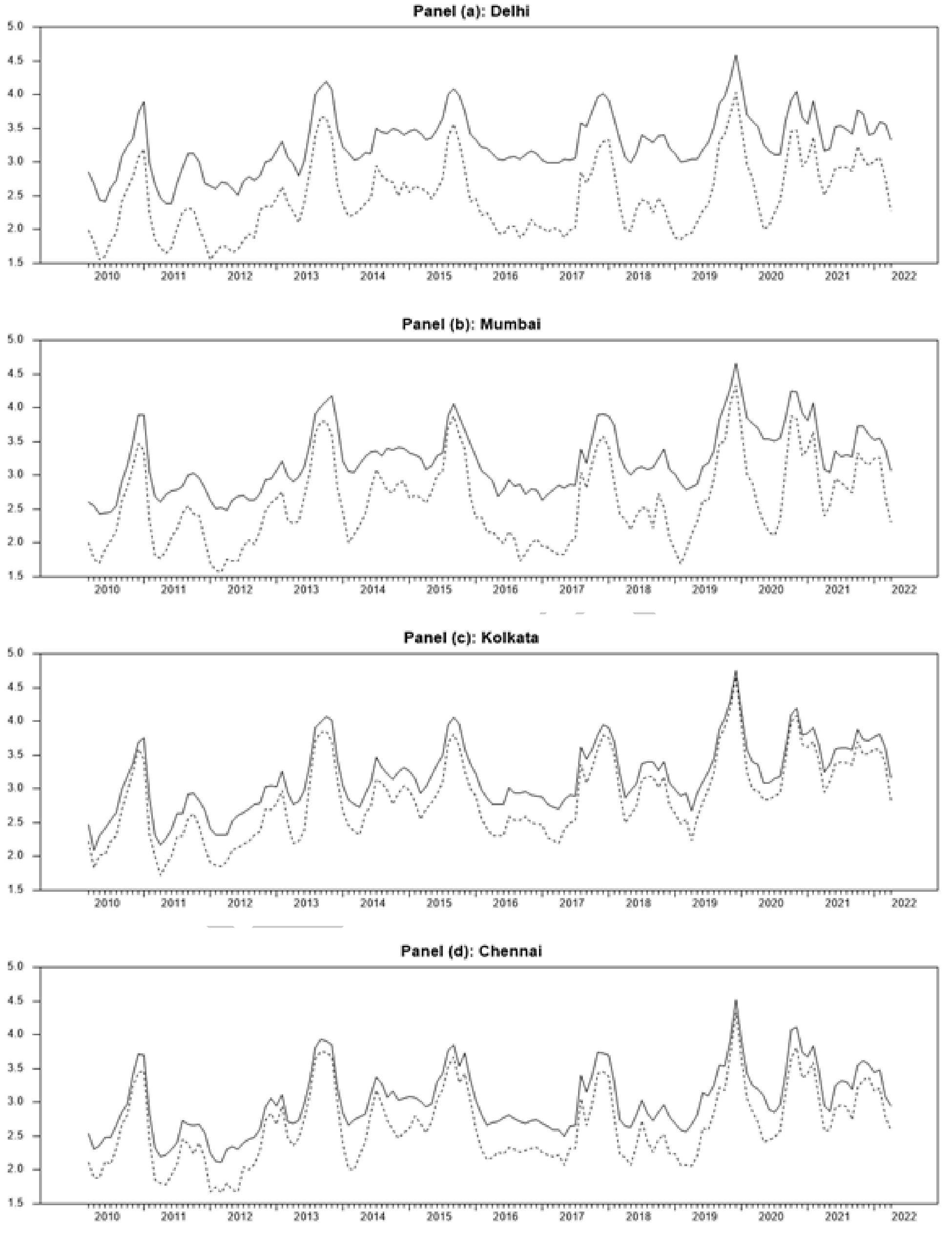

Figure 1. Wholesale and Retail Prices of Onions in Major Indian Cities (logged)

Notes: The solid lines denote retail prices, and the dotted lines denote wholesale prices. The sample period is shown on the horizontal axis, and the logged values of prices are on the vertical axis.

contribute to the irregular arrival patterns of onions in the market. To provide a visual representation of onion availability over time in the four different cities, please refer to Figure 2.

The availability of onions exhibits significant variations among the different cities, with Kolkata and Chennai consistently receiving lower levels of onion arrivals over time when compared to Mumbai and Delhi.[4] For a visual representation of the rainfall deviation, as previously defined,

[4] As with prices, we construct the variance plot for the arrivals of onions in the four major cities. Except for Chennai, there is no clear signs of non-stationary volatility. The results are in Figure A.1 in the Appendix.

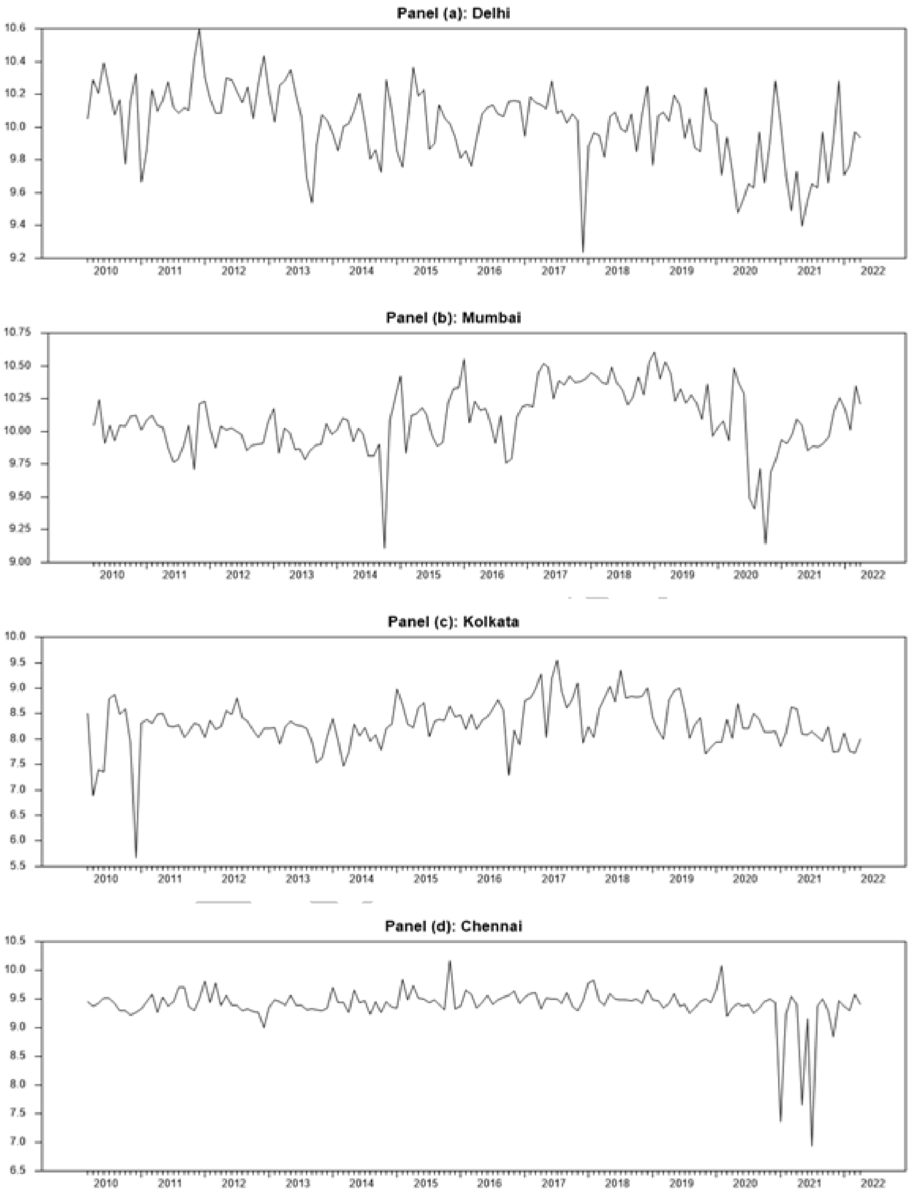

Figure 2. Arrivals of Onions in Major Indian Cities (logged)

Notes: The sample period is shown on the horizontal axis, and the logged values of supplies (quantities in kilograms) of onions are on the vertical axis.

please refer to Figure 3. Notably, our analysis reveals a substantial escalation in the magnitude and frequency of rainfall deviation in recent years, particularly starting from 2020 onwards.

The occurrence of rainfall anomalies, especially since 2020, has been documented in recent studies by Darshana et al. (2024) and Mandke and Vaisakh (2025). The period from 2020 coincides with the triple-dip La Nina period that may have led to significant rainfall variations.

Accordingly, we have identified the period from March 2020 to the end of our dataset as a 'reference time frame.' During this interval, we will conduct an analysis to assess the impact of average rainfall deviations on the wholesale and retail prices of onions, as well as onion arrivals, in the four major cities. To provide a point of comparison, we will contrast these findings with a

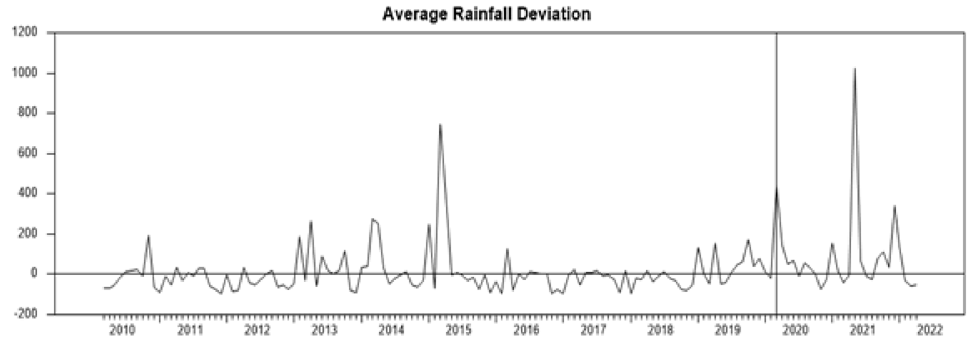

Figure 3. Average Rainfall Deviation in Selected Indian states

Notes: The source of the data is the Indian Meteorological Department (IMD) from where we obtain monthly rainfall deviation computed as the normal rainfall (which is set by the IMD) subtracted from actual rainfall for each individual onion producing state. We compute average rainfall deviation data as shown in the figure by averaging the rainfall deviation across the onion producing states. The numbers on the vertical axis measure the percentage deviations and on the horizontal axis we plot the time span in monthly frequency from March 2010 to April 2022.

Table 1. Descriptive Statistics

	Mean	S.D.	CV	Skewness	Kurtosis	Normality
Panel A. Delhi						
P_t^R	29.41	13.99	0.475	1.60 [0.00]	3.84 [0.00]	152.81 [0.00]
P_t^W	13.88	8.77	0.631	1.79 [0.00]	4.01 [0.00]	176.87 [0.00]
A_t	22883.85	4946.82	0.216	0.06 [0.65]	0.32 [0.43]	0.84 [0.65]
Panel B. Mumbai						
P_t^R	28.57	15.57	0.545	1.72 [0.00]	3.96 [0.00]	167.64 [0.00]
P_t^W	16.47	12.80	0.728	1.93 [0.00]	4.71 [0.00]	226.92 [0.00]
A_t	24731.29	5934.96	0.239	0.29 [0.14]	-0.04 [0.91]	2.15 [0.34]
Panel C. Kolkata						
P_t^R	27.69	15.68	0.566	1.89 [0.00]	6.19 [0.00]	321.06 [0.00]
P_t^W	21.13	14.34	0.678	2.13 [0.00]	7.63 [0.00]	465.50 [0.00]
A_t	4437.56	2031.78	0.457	1.51 [0.00]	3.77 [0.00]	142.30 [0.00]
Panel D. Chennai						
P_t^R	23.09	12.81	0.554	1.88 [0.00]	5.39 [0.00]	262.72 [0.00]
P_t^W	16.55	10.74	0.648	1.99 [0.00]	6.08 [0.00]	322.63 [0.00]
A_t	12660.63	2859.97	0.226	0.16 [0.42]	7.95 [0.00]	383.10 [0.00]

Notes: P_t^R,P_t^W and A_t denote retail prices, wholesale prices and availability of onions respectively. Square brackets indicate p-values associated with statistical significance. CV stands for coefficient of variation.

counterfactual scenario in which no rainfall deviations occur, essentially representing normal rainfall conditions.

To facilitate this analysis, we use the forecasts generated by the VAR-X, enabling us to quantify the percentage changes in onion prices and arrivals for the four different cities attributed to these rainfall anomalies.

We have calculated several key statistical measures, including the coefficient of variation (defined as the ratio of the standard deviation to the mean), skewness, excess kurtosis, and conducted a normality test (specifically, the Jarque-Bera test). A summary of the descriptive statistics for the data employed in this study is presented in Table 1 below.

Since we expect retail prices to carry a markup over wholesale prices, it is not unusual to find that the mean of retail prices is higher than the that of wholesale prices. We note that the standard deviation of retail prices is higher than that of wholesale prices. Across all cities, both retail and wholesale prices exhibit a notable degree of variability, ranging approximately between 50% to 70%. In contrast, the arrivals of onions remain relatively stable, hovering around 22%. However, it's worth noting that Kolkata stands out with significantly higher variability, almost double that of the other cities, at approximately 45%.

For all the cities, both retail and wholesale prices display positive skewness, indicating that positive price spikes are more pronounced and prevalent than negative ones. This observation aligns with our earlier discussion, highlighting the tendency for prices to spike when inventories are running low or when there is a poor harvest.

In terms of kurtosis, we observe significant values in the prices, suggesting the presence of extreme values. However, when it comes to arrivals, we find that Kolkata and Chennai exhibit extreme values, in contrast to Delhi and Mumbai, where the distribution appears less extreme. Furthermore, our analysis indicates that the distribution of arrivals is not normal for Kolkata and Chennai, whereas Delhi and Mumbai exhibit a normal distribution.

The variations in skewness, kurtosis, and the distribution of onion arrivals across the four markets can likely be attributed to differences in their roles as major or minor onion-producing states, as well as the number of onion-producing centers from which they source their supply. Mumbai, situated in the largest onion-producing state, Maharashtra, receives onions directly from this prolific source. On the other hand, Delhi, while not a significant onion-producing region itself, draws its onion supply from four major onion-producing states: Maharashtra, Madhya Pradesh, Rajasthan, and Gujarat. In contrast, Chennai, located in Tamil Nadu, and Kolkata, situated in West Bengal, are not part of any major onion-producing states. Chennai receives onions from two onion-producing states, namely Maharashtra and Karnataka, while Kolkata relies primarily on Maharashtra for its onion supply (Gulati, Wardhan, and Sharma, 2022).

This information is visually represented in the map featured in Figure 4. It is plausible that due to the advantage of either being situated in a major onion-producing state or receiving onions from multiple onion-producing states, Mumbai and Delhi may experience more consistent patterns in onion arrivals when compared to Chennai and Kolkata.

Empirical Strategy

We have developed a dynamic model that incorporates retail and wholesale prices of onions, as well as onion arrivals. In this model, retailers base their retail pricing decisions on their observations of wholesale onion prices and onion arrivals. The retail price is typically set as a mark-up over the prevailing wholesale price. The magnitude of this mark-up in retail prices over wholesale prices is contingent upon the number of intermediaries involved between the wholesale and retail stages of the trade.

Wholesalers play a pivotal role in this process. They determine the prices at which they purchase onions from growers during harvest seasons and subsequently distribute most of these onions to retailers, while retaining a smaller quantity in storage. This stored inventory is periodically released to the market until the next harvest season when a fresh supply of onions becomes available. For wholesalers, the challenge lies in deciding the quantity to procure during the harvest season and the quantity to retrieve from storage. These decisions must account for various factors, including storage costs, product deterioration, and expectations of future price movements.

Structural Setting for the Onion Market

The arrivals of onion supply, denoted as A_t, are subject to fluctuations stemming from variations in production and storage levels in the preceding period. Notably, there is no contemporaneous

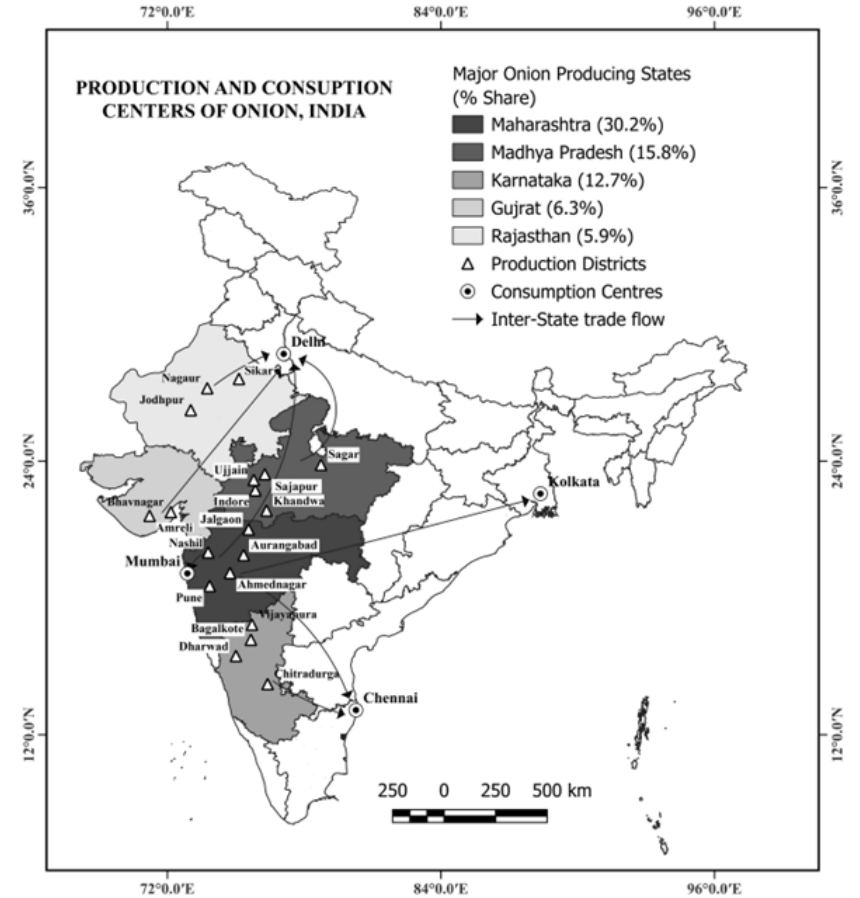

Figure 4. Geographical Distribution of Major Onion Producing States of India

correlation between these arrivals and onion prices, whether at the wholesale or retail level. This is largely attributed to the perception that the demand for onions is characterized by a high degree of inelasticity.

In this framework, both wholesale and retail prices are influenced by current and past arrivals, while retail prices are affected by current and lagged wholesale prices. In major cities, wholesale traders have access to storage facilities. During adverse weather conditions, stock hoarding practices become prevalent. This hoarding behavior impacts arrivals, creating supply shortages during such periods. Subsequently, these stored onions are released into the market when wholesale and retail prices from previous periods are at elevated levels, with the aim of maximizing profits.

Based on these dynamics, we can formulate the structural model for the onion market as follows:

$$P_t^R = \beta P_t^W + \rho A_t + \sum_{i=1}^{k} \phi_{RRi} P_{t-i}^R + \sum_{i=1}^{k} \phi_{RWi} P_{t-i}^W + \sum_{i=1}^{k} \phi_{RAi} A_{t-i} + \eta_t^R \tag{1}$$

$$P_t^W = \zeta A_t + \sum_{i=1}^{k} \phi_{WRi} P_{t-i}^R + \sum_{i=1}^{k} \phi_{WWi} P_{t-i}^W + \sum_{i=1}^{k} \phi_{WAi} A_{t-i} + \eta_t^W \tag{2}$$

$$A_t = \sum_{i=1}^{k} \phi_{ARi} P_{t-i}^R + \sum_{i=1}^{k} \phi_{AWi} P_{t-i}^W + \sum_{i=1}^{k} \phi_{AAi} A_{t-i} + \eta_t^A \tag{3}$$

where P_t^R,P_t^W and A_t denote retail prices, wholesale prices and availability of onions respectively. The error term η_t^A in (3) is seen as a structural arrival shock to the onion market and it causes an increase in both arrivals and prices (retail and wholesale) through the contemporaneous correlation in equations (1) and (2). The structural error terms η_t^W and η_t^R can be seen as the wholesale price-specific shock and the retail price-specific shock respectively. Price-specific shocks is possible as we allow for a highly inelastic demand curve for onions. The structural error terms η_t^R, η_t^W and η_t^A are white noise, uncorrelated with constant standard deviations σ^R, σ^W and σ^A, respectively.

Given that wholesale prices, retail prices, and arrivals of onions interact with each other, they can be couched in a reduced form VAR model so that the model can be estimated using OLS. The VAR model takes the form:

$$\begin{bmatrix} P_t^R \\ P_t^W \\ A_t \end{bmatrix} = \begin{bmatrix} A_{01} \\ A_{02} \\ A_{03} \end{bmatrix} + \begin{bmatrix} A_{11}(L) & A_{12}(L) & A_{13}(L) \\ A_{21}(L) & A_{22}(L) & A_{23}(L) \\ A_{31}(L) & A_{32}(L) & A_{33}(L) \end{bmatrix} \begin{bmatrix} P_{(t-1)}^R \\ P_{(t-1)}^W \\ A_{(t-1)} \end{bmatrix} + \begin{bmatrix} \epsilon_{1t} \\ \epsilon_{2t} \\ \epsilon_{3t} \end{bmatrix} \tag{4}$$

which allow the expressions A_{ij}(L) to be polynomials in the lag operator L, and ϵ_{kt} (k = 1, 2, 3) are the reduced form VAR errors which may be correlated. The nature of the VAR-X system is such that the variables P_t^R, P_t^W, A_t are jointly determined. The relationship between the structural form and reduced form errors can be set out as:

$$\begin{bmatrix} 1 & -\beta & -\rho \\ 0 & 1 & -\zeta \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} \epsilon_{1t} \\ \epsilon_{2t} \\ \epsilon_{3t} \end{bmatrix} = \begin{bmatrix} \eta_t^R \\ \eta_t^W \\ \eta_t^A \end{bmatrix} \tag{5}$$

The upper triangular matrix in (5) shows a Cholesky decomposition of the reduced form errors.

Vector Autoregression with Exogenous Variable Model

Onions, being a storable commodity, exhibit price dynamics that are not solely influenced by the quantity of onion arrivals available for release from storage to prevent stock-outs. The central focus of this paper is to investigate the impact of rainfall anomalies, treated as exogenous, on onion arrivals, as well as on wholesale and retail prices.

To achieve this empirical investigation, we adopt the VAR-X framework, which allows us to analyze the relationships between onion arrivals, wholesale and retail prices, and rainfall anomalies. Within this framework, we treat rainfall deviations (the disparity between actual and normal rainfall levels) as exogenous variables denoted as X. This approach ensures that there is no feedback from the endogenous variables to rainfall deviations, enabling us to isolate the external influence of rainfall anomalies on the variables of the model.

Given the challenges associated with forecasting from unrestricted VAR models, which can often suffer from over-parameterization, an alternative approach has emerged to enhance forecasting accuracy. This approach involves the addition of a vector of exogenous variables into the VAR system. These VAR-X models have gained prominence in the field of economics, as evidenced by notable studies such as those conducted by Cushman and Zha (1997) and Eckstein and Tsiddon (2004).

Accordingly, we set out our VAR-X model with $z_t = \begin{bmatrix} P_t^R & P_t^W & A_t \end{bmatrix}'$ being the vector of endogenous variables comprising retail prices, wholesale prices and availability of onions. The vector R_T denotes an exogenous vector of rainfall deviations. The VAR-X builds on (4) to take the following form:

$$\begin{bmatrix} P_t^R \\ P_t^W \\ A_t \end{bmatrix} = \begin{bmatrix} A_{01} \\ A_{02} \\ A_{03} \end{bmatrix} + \begin{bmatrix} A_{11}(L) & A_{12}(L) & A_{13}(L) \\ A_{21}(L) & A_{22}(L) & A_{23}(L) \\ A_{31}(L) & A_{32}(L) & A_{33}(L) \end{bmatrix} \begin{bmatrix} P_{(t-1)}^R \\ P_{(t-1)}^W \\ A_{(t-1)} \end{bmatrix} + \begin{bmatrix} c_R R_{t-1} \\ c_W R_{t-1} \\ c_A R_{t-1} \end{bmatrix} + \begin{bmatrix} \epsilon_{1t} \\ \epsilon_{2t} \\ \epsilon_{3t} \end{bmatrix} \tag{6}$$

where the parameters c_k (k = R, W, A) measure the influence of lagged rainfall deviations on the variables in the vector z_t. The nature of the VAR-X system is such that the exogenous variable R_T is allowed to affect all the other three endogenous variables and that there is no feedback from the endogenous variables to rainfall deviations. The lag length of the VAR-X is chosen according to the Bayesian Information Criterion (BIC) to provide the best fit to the data.

The three equations of the model are estimated across the entire sample from March 2010 to April 2022. From the parameter estimates obtained using (6) one can test for Granger causality by placing appropriate restrictions on the A_{ij}(L) polynomials. For example, one can set up the null hypothesis of Granger non causality that retail prices do not Granger cause wholesale prices (that is, $P_t^R \nRightarrow P_{t+i}^W$ by placing the restriction $H_0 : (A_{21}(L) = 0)$. Rejecting the null would imply that current retail prices can be used to make short-term prediction on wholesale prices.

We use the VAR-X to make out of sample forecasts using the exogenous vector of variables so that we can quantify the effect of the exogenous variables on the system of endogenous variables in the system. We adopt the approach by Eckstein and Tsiddon (2004) to specify the time path of the rainfall deviation variable. To illustrate their method, we first start out with a standard VAR model. Consider a simple first order VAR:

$$z_t = A_0 + A_1 z_{t-1} + e_t \tag{7}$$

If the sample size is given by T, then one can obtain 1-step ahead forecasts by using the conditional expectation operator to get:

$$E_T(z_{T+1}) = A_0 + A_1 z_T \tag{8}$$

Using a recursive approach one can obtain the 2-step ahead forecast as:

$$E_T(z_{T+2}) = A_0 + A_1[A_0 + A_1 z_T] \tag{9}$$

In this recursive manner, we can obtain the j-step ahead forecasts as:

$$E_T(z_{T+j}) = A_0[I + A_1 + A_1^2 + \dots + A_1^{j-1}] + A_1^j z_T \tag{10}$$

However, given the over-parameterisation problem that we have already mentioned, we adopt the VAR-X model in the spirit of Eckstein and Tsiddon (2004) and estimate the following VAR-X model of order 1, given by:

$$z_t = A_0 + A_1 z_{t-1} + cR_{t-i} + e_t \tag{11}$$

where c is a 3ÃŮ1 vector $\begin{bmatrix} c_R & c_W & c_A \end{bmatrix}'$ of parameters. In this case, the 1-step ahead forecast is given by:

$$E_T(z_{T+1}) = A_0 + A_1 z_T + cR_T \tag{12}$$

and the two-step ahead forecast is given recursively by:

$$E_T(z_{T+2}) = A_0 + A_1[E_T(z_{T+1} + cR_{T+1})] \tag{13}$$

From equation (13) we can see that to forecast z_{T+2} and beyond it is necessary to know the magnitude of the rainfall deviation variable over the forecast period. The reference time frame and the out-of-sample forecasting are over two separate time periods. We chose the reference time-frame which is in-sample data because of the more frequent rainfall anomalies that took place during this period. This spans a 26-month period from March 2020 to April 2022. We then choose an out-of-sample period to generate the forecasts of the onion prices as well as supplies for another 26-month (out of sample) period from May 2022 to June 2024. The procedure we use follows Eckstein and Tsiddon

(2004) by assuming that there is no rainfall deviation (R_j) from May 2022 onwards so that all values of $R_j = 0$ for $j >$ April 2022 and generate the forecasts over a 26-month (out-of-sample) period up to June 2024. We then take the average rainfall deviation over the last 26 months (from March 2020 to April 2022) of the sample period and set this period average to be the values of R_j for the reference time frame (i.e., average from March 2020 to April 2022) and set this over the time period May 2022 to June 2024 for $j >$ April 2022 over the forecast period. The forecasts over a 26-month period for P_t^R, P_t^W, A_t up to June 2024 are generated. Once we have the out of sample forecasts, we calculate the average of each variable forecast of P_t^R, P_t^W, A_t to compare what values these variables would take with no rainfall deviation (no RD) and with rainfall deviation (with RD). This procedure would allow us to measure and compare the impact of rainfall deviation on the prices and availability of onions.

Finally, we carry out innovation accounting to obtain the impulse response analysis. We analyse the behaviour of the P_t^R, P_t^W, A_t variables in response to shocks to each of these variables as well as rainfall deviations. To this end, we obtain the vector moving average (VMA) from the VAR-X given by (6) as follows:

$$(14)\quad \begin{bmatrix} P_t^R \\ P_t^W \\ A_t \end{bmatrix} = \begin{bmatrix} \bar{P}^R \\ \bar{P}^W \\ \bar{A} \end{bmatrix} + \sum_{i=0}^{m} \begin{bmatrix} \psi_{11}(i) & \psi_{12}(i) & \psi_{13}(i) \\ \psi_{21}(i) & \psi_{22}(i) & \psi_{23}(i) \\ \psi_{31}(i) & \psi_{32}(i) & \psi_{33}(i) \end{bmatrix} \begin{bmatrix} \eta_{t-i}^R \\ \eta_{t-i}^W \\ \eta_{t-i}^A \end{bmatrix} + \sum_{i=0}^{m} \begin{bmatrix} \phi_{11}(i) & \phi_{12}(i) & \phi_{13}(i) \\ \phi_{21}(i) & \phi_{22}(i) & \phi_{23}(i) \\ \phi_{31}(i) & \phi_{32}(i) & \phi_{33}(i) \end{bmatrix} \begin{bmatrix} R_{t-1-i} \\ R_{t-1-i} \\ R_{t-1-i} \end{bmatrix}$$

or, more compactly as:

$$(15)\qquad z_t = \bar{z} + \sum_{i=0}^{m} \psi_i \eta_{t-i} + \sum_{i=0}^{m} \phi_i R_{t-1-i}$$

with $z_t = \begin{bmatrix} P_t^R & P_t^W & A_t \end{bmatrix}'$ the coefficients of ψ_i can be used to generate the effects of η_{Rt}, η_{Wt} and η_{At} shocks on the P_t^R, P_t^W, A_t variables. The impulse response function trace out the $\psi(i)$ coefficients against a set time horizon ($i = 1, 2, \ldots, H$) would allow us to plot the time path of P_t^R, P_t^W, A_t variables in response to shocks in η_{Rt}, η_{Wt} and η_{At}. Further, we can use the impulse response function to trace out the response of P_t^R, P_t^W, A_t variables in response to shocks in rainfall deviation given by the $\phi(i)$ coefficients to a shock in R_{t-1-i}.

Empirical Results

In this section, we present our empirical estimations. To prepare for the VAR-X estimation, we conduct unit root tests on the variables, both with and without the inclusion of a linear deterministic trend. It is widely recognized that these tests may suffer from low statistical power when additional deterministic terms are present. In addressing this issue of low power, we employ more powerful testing procedures, including those proposed by Elliott, Rothenberg, and Stock (1996). These procedures include the GLS de-trended version of the standard Augmented Dickey-Fuller (ADF) test and the point optimal procedure. The results of these tests are presented in Table 2 below.

For all the variables considered, we find that the estimated statistics are less than the critical values implying that we reject the null hypothesis of a unit root and conclude the variables are stationary I(0).[5] The lag lengths, selected according to the BIC, are in parentheses. Given that the variables are stationary I(0), we conclude that any shocks to onion prices are transitory in nature.[6]

[5] Based on the plots in Figures 1 and 2, we also consider the possibility of unit root tests allowing for non-stationary volatility as well as seasonal unit roots. These are carried out as robustness tests to clarify there is no unit root at seasonal frequencies nor with non-stationary volatility. The results based on the popular seasonal unit root test due to Hylleberg et al. (1990) and the unit root test with nonstationary volatility (Smeekes and Taylor, 2012) are shown in tables A.2 and A.3 in the Appendix.

[6] The VAR-X model is stable with stationary I(0) variables as shown by the plot of eigenvalues of characteristic polynomial in unit circle given in Figure A.2 in the Appendix.

Table 2. Unit Root Test Results

Panel A	Augmented Dickey-Fuller (ADF test)							
	Delhi		Mumbai		Kolkata		Chennai	
	With Trend	No Trend	With Trend	No Trend	With Trend	No Trend	With Trend	No Trend
P_t^R	$-5.64(1)^a$	$-4.96(1)^a$	$-4.83(1)^a$	$-4.43(1)^a$	$-5.79(1)^a$	$-5.01(1)^a$	$-5.42(1)^a$	$-4.93(1)^a$
P_t^W	$-5.35(1)^a$	$-5.03(1)^a$	$-5.30(1)^a$	$-5.12(1)^a$	$-5.82(1)^a$	$-4.97(1)^a$	$-5.33(1)^a$	$-5.03(1)^a$
A_t	$-9.18(0)^a$	$-7.47(0)^a$	$-5.76(0)^a$	$-5.65(0)^a$	$-6.34(0)^a$	$-4.51(0)^a$	$-10.9(0)^a$	$-2.48(5)^c$
RD_t	$-10.24(0)^a$							
Panel B	Elliott, Rothenberg and Stock DF-GLS (ERS test)							
	Delhi		Mumbai		Kolkata		Chennai	
	With Trend	No Trend	With Trend	No Trend	With Trend	No Trend	With Trend	No Trend
P_t^R	$-5.64(1)^a$	$-3.79(1)^a$	$-4.68(1)^a$	$-2.99(1)^a$	$-5.55(1)^a$	$-3.11(1)^a$	$-5.39(1)^a$	$-3.76(1)^a$
P_t^W	$-5.34(1)^a$	$-4.04(1)^a$	$-5.20(1)^a$	$-3.96(1)^a$	$-5.81(1)^a$	$-3.62(1)^a$	$-5.26(1)^a$	$-3.87(1)^a$
A_t	$-9.18(0)^a$	$-2.08(0)^a$	$-5.63(0)^a$	$-4.54(0)^a$	$-6.35(0)^a$	$-1.33(0)^a$	$-10.9(0)^a$	$-2.45(5)^b$
RD_t	$-8.55(0)^a$							
Panel C	Elliott, Rothenberg and Stock Point Optimal (PT tests)							
	Delhi		Mumbai		Kolkata		Chennai	
	With Trend	No Trend	With Trend	No Trend	With Trend	No Trend	With Trend	No Trend
P_t^R	$1.53(1)^a$	$1.01(1)^a$	$2.23(1)^a$	$1.59(1)^a$	$1.70(1)^a$	$1.65(1)^a$	$1.72(1)^a$	$1.00(1)^a$
P_t^W	$1.69(1)^a$	$0.81(1)^a$	$1.83(1)^a$	$0.85(1)^a$	$1.49(1)^a$	$1.13(1)^a$	$1.78(1)^a$	$0.94(1)^a$
A_t	$1.37(0)^a$	$0.62(0)^a$	$2.19(0)^a$	$0.93(0)^a$	$1.83(0)^a$	$2.18(0)^a$	$1.26(0)^a$	$3.92(0)^c$
RD_t	$0.45(0)^a$							

Notes: numbers enclosed in parentheses signify the lag length selected through the Bayesian Information Criterion (BIC). The superscripts 'a,' 'b,' and 'c' indicate the rejection of the null hypothesis at the 1%, 5%, and 10% significance levels, respectively. The variable RD_t represents rainfall deviation, derived as the discrepancy between actual rainfall and the normative rainfall levels in the primary onion-producing states. Additionally, in the equations, P_t^R signifies retail prices, P_t^W stands for wholesale prices, and A_t denotes onion availability.

Table 3. Granger causality test results from VAR-X model

	Granger Causality Test Results from VAR-X Model			
	Delhi	Mumbai	Kolkata	Chennai
$P_t^W \nRightarrow P_{t+i}^R$	$7.605\ [0.000]^a$	$12.908\ [0.000]^a$	$11.537\ [0.001]^a$	1.886 [0.171]
$A_t \nRightarrow P_{t+i}^R$	0.449 [0.638]	0.782 [0.377]	$2.989\ [0.086]^c$	$4.241\ [0.041]^b$
$P_t^R \nRightarrow P_{t+i}^W$	0.280 [0.756]	$4.648\ [0.032]^b$	$5.949\ [0.016]^b$	0.272 [0.602]
$A_t \nRightarrow P_{t+i}^W$	0.354 [0.702]	$3.492\ [0.063]^c$	$3.634\ [0.058]^c$	$3.278\ [0.072]^c$
$P_t^R \nRightarrow A_{t+i}$	1.056 [0.351]	0.374 [0.541]	$3.341\ [0.069]^c$	0.061 [0.805]
$P_t^W \nRightarrow A_{t+i}$	0.363 [0.696]	0.884 [0.348]	$4.269\ [0.040]^b$	0.043 [0.834]

Notes: Numbers in square brackets denote the probability values. The null hypothesis is Granger non-causality, e.g., $P_t^R \nRightarrow P_t^W$ denotes retail price does not Granger-cause wholesale process. The superscripts ^{a} , ^{b} and ^{c} denotes rejection of the null hypothesis at the 1%, 5% and 10% significance levels respectively.

Therefore, even though the prices may be punctuated by occasional spikes, the shocks are short-lived, leading to infer that government intervention may prevent shocks being long-lived.

We conduct Granger casuality tests using the parameter estimates of the VAR-X model that we propose in (6) for the four individual cities.[7] The lag lengths are chosen according to the BIC. Placing appopriate restrictions on the parameter estimates (as described in the earlier section), we test the null hypothesis of Granger non-causality between the endogenous variables included in the VAR-X, and report the estimated F-statistics along with their associated probability values in square brackets in Table 3 below.

[7] The parameter estimates of the VAR-X model are given in Table A.4 in the Appendix. The results show the significance of the exogenous variable. Being rainfall deviation, in each of the VAR models for the individual cities. We also report the tests for serial correlation in Table A.5 in the Appendix, by using the Edgeworth expansion corrected Likelihood ratio test (LRE) and the Rao F-statistic. The results show the VAR-X model passes the diagnostic tests.

Table 4. Forecast from the VAR-X Model

	Delhi		Mumbai		Kolkata		Chennai	
	No RD	With RD	No RD	With RD	No RD	With RD	No RD	With RD
$fi\_P_t^R$	3.23	3.33	3.14	3.30	3.16	3.25	2.98	3.14
% (−/+)	+10.51		+17.35		+9.41		+17.35	
$fi\_P_t^W$	2.38	2.47	2.49	2.66	2.83	2.93	2.60	2.78
% (−/+)	+9.41		+18.53		+10.51		+19.72	
fi_A_t	10.02	9.89	10.10	10.07	8.31	8.31	9.43	9.35
% (−/+)	-12.19		-2.95		0		-7.68	

Notes: The notations fi where i=1 (no RD) and 2 (with RD) represent the mean values computed over the out-of-sample forecast period for retail prices, wholesale prices, and arrivals, respectively. The notation % $(-/+)$ indicates the percentage decrease or increase, respectively, when considering the scenario without any rainfall anomalies and when assuming the average rainfall anomalies observed over the past 26 months.

The results exhibit significant variability across all the cities, as indicated by the p-values enclosed in square brackets. In the case of Delhi, the only discernible causal relationship identified is from wholesale prices to retail prices. In the case of Mumbai, we detect feedback effects, indicating bidirectional causality between retail and wholesale prices. Conversely, for Chennai, our findings suggest that arrivals play a causal role in influencing both retail and wholesale prices. In stark contrast, we find that for Kolkata all variables demonstrate causal relationships with each other. Bidirectional causality exists between wholesale and retail prices, as well as between arrivals and both retail and wholesale prices.

Given the expectation that retail prices carry a mark-up over wholesale prices, it's unsurprising that wholesale prices influence retail prices, with Chennai being the sole exception. In the case of Mumbai and Kolkata, we identify bidirectional causality with retail prices influencing wholesale prices. The observation that wholesale prices lead retail prices in these two cities implies a rapid incorporation of market signals from retail points.

Notably, Chennai and Kolkata stand out as the two cities where we observe arrivals exerting a predictive influence on both retail and wholesale prices. This phenomenon may be explained by differences in storage facilities and transportation costs of onions for Chennai and Kolkata on one hand, and Mumbai and Delhi on the other. The rapid transmission of information between arrivals and prices in Kolkata could provide insights into the bidirectional causality observed in this market.

The estimation of a VAR-X allows us to proceed towards analyzing how rainfall anomalies affect retail and wholesale prices of onions as well as the arrivals. We first estimate the VAR-X model and then estimate the impact over the forecast horizon by conducting a 26- month out of sample period.

In accordance with the methodology outlined in the previous section, we adhere to the approach proposed by Eckstein and Tsiddon (2004). Specifically, we assume that there are no rainfall deviations from May 2022 to June 2024, which implies that all values of R_j equal 0 for $j >$ April 2022. Subsequently, we generate forecasts using the VAR-X model for both retail and wholesale onion prices, as well as onion arrivals, spanning the 26-month period leading up to June 2024.

To summarize the outcomes, we calculate the average of each forecasted variable, denoted as f1_P_t^R, f1_P_t^W, and f1_A_t, over the 26-month duration. These results are presented in Table 4 under the sub-column labeled 'No RD,' signifying 'no rainfall deviation.'

Next, we compute the average rainfall deviation observed over the last 26 months of the sample period and assign these average values to R_j for $j >$ April 2022 throughout the forecast period. Similar to our previous approach, we estimate forecasts over a 26-month horizon, extending up to June 2024, for each variable, denoted as $f2\_P_t^R$, $f2\_P_t^W$, and $f2\_A_t$. Subsequently, we calculate the mean values of these forecasts over the 26-month timeframe. These results are presented in Table 4, under the sub-column labeled 'With RD,' signifying 'with rainfall deviation.'

When comparing the forecasted prices at both the retail and wholesale levels, we observe that, for each city, prices in scenarios with no rainfall deviation are lower on average than those with average rainfall deviations. This implies that rainfall deviations exert upward pressure on prices. Additionally, we find that rainfall anomalies lead to a reduction in available onion supplies. As our price data is in logarithmic form, we calculate the average percentage increase in prices for all cities attributable to rainfall deviations, in comparison to a counterfactual scenario without any rainfall deviation.

Our findings indicate that when the average of rainfall anomalies over the last 26 months is incorporated into the VAR-X model, the forecasted retail and wholesale prices increase. The upward pressure on both retail and wholesale prices falls within a range of 9% to 19% for all the cities. Notably, in the cases of Kolkata and Delhi, the price increase for both retail and wholesale prices is nearly identical, approximately ranging from 9% to 11%. Conversely, for Mumbai and Chennai, the increase is relatively higher, concentrated around 17% to 19%, with wholesale price increases slightly exceeding retail price increases. Furthermore, rainfall anomalies lead to a decrease in arrivals of onions, ranging from approximately 3% to 12%, except for Kolkata, where arrivals remain unaffected.

In broad terms, we can conclude that rainfall anomalies indeed exert upward pressure on both retail and wholesale prices, although the extent varies across different cities. This may imply that the retrieval of onions from storage, rather than relying solely on production and harvest, is more readily practiced in Delhi and Kolkata compared to Mumbai and Chennai. The lower price effects observed in the former two cities suggest that inventory retrievals are likely to be prompt. It is evident that rainfall deviations have an impact on arrivals, albeit to a lesser degree. Erratic rainfall can result in poor harvests and consequently a potential decrease in arrivals. However, this decline in arrivals can be offset by an increase in retrievals from storage, a phenomenon more apparent in the case of Kolkata.

To trace out the effects of how retail, wholesale prices and arrivals of onions respond to rainfall shocks, we conduct an impulse response analysis using the VAR-X framework. Using the framework given by equation (6) we trace out the response of the P_t^R, P_t^W, A_t variables in response to shocks in rainfall. The response of all the three variables to rainfall shocks for each of the individual cities, are depicted in Figure 5 below.

In the Delhi market, a rainfall shock initially does not impact retail prices, but after one month, the price of onions at the retail level begins to rise. This upward trend continues for two months, reaching a peak before gradually decreasing and becoming insignificant after six months. Wholesale prices in Delhi follow a similar pattern with no initial impact, followed by a gradual significant response, peaking after two months and then dissipating over five months. Arrivals in Delhi also show no initial impact, but after two months, a gradual decline becomes noticeable, lasting about five months.

For Mumbai, there is no initial impact of a rainfall shock on prices, but in the first month following the shock, both retail and wholesale prices experience a relatively sharp increase in response to rainfall shocks, with the rise occurring within a month. However, the decline afterward is gradual, particularly in the case of retail prices, lasting at least 9 months. The shock does not have an immediate impact on arrivals, but within a month there is an initial decrease and then a quick recovery to their original level after two months. In Kolkata, the response functions for retail and wholesale prices resemble those in Mumbai, but they dissipate quickly, approximately within five months. Arrivals in Kolkata do not exhibit a significant response to rainfall shocks. In the Chennai market, retail and wholesale prices respond similarly to those in other cities, with no initial impact, followed by an increase and then a decrease. However, the response remains significant even after 11 months. Onion arrivals in Chennai are sharply affected, with a noticeable decrease in availability within a month following a rainfall shock. This decrease is short-lived, as arrivals return to their original level within two months.

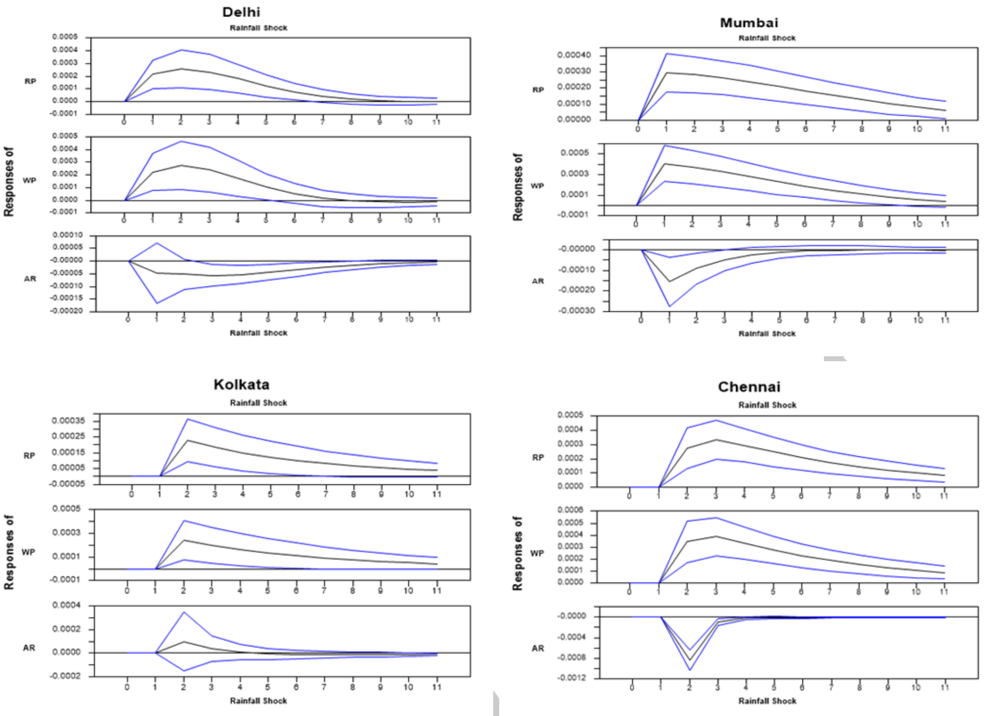

Figure 5. Impulse Response Analysis of Rainfall Shocks

Notes: The horizontal axis denotes the chosen time horizon; in this case 12 months. The initial period (0) does not include any response as the rainfall effect is lagged by construction. The remaining 11 months is the horizon that we examine. The black line is the response function, whereas the associated blue lines are the 90% confidence intervals. The vertical axis measures the impact of the shock on the variables in growth form. To this end RP, WP, and AR stand for retail price, wholesale price, and arrivals, respectively.

In summary, for all cities, both retail and wholesale prices initially do not respond to rainfall shocks, but they later experience a sharp increase followed by a gradual decrease. The duration for the shock's impact on prices varies among cities, with Chennai and Mumbai exhibiting relatively long-lived effects compared to Delhi and Kolkata. Arrivals respond differently to rainfall shocks. Chennai and Mumbai show a clear dip in arrivals, especially pronounced in Chennai. In contrast, while there is a slight negative effect on arrivals after about three months for Delhi, there is no significant impact on arrivals in Kolkata.

We then proceed to compute the responses of retail, wholesale prices, and arrivals of onions in response to shocks in retail, wholesale prices, and arrivals of onions. The corresponding graphs illustrating these responses are presented in Figure 6 below.

The impulse responses in Delhi, Chennai, and Mumbai demonstrate minimal to no reaction in wholesale prices and onion arrivals to shocks in retail prices. In the case of Kolkata, a shock to retail prices induces a slight, lagged, and transitory response in wholesale prices, while arrivals exhibit a similar but positive response. Across all cities, retail prices react similarly to shocks in wholesale prices. Initially, the response is positive, with the impact of the shock diminishing over time. However, arrivals do not display any significant response to wholesale price shocks, except for Delhi and Kolkata, where it is slightly negative, lagged, and transitory.

Both retail and wholesale prices respond negatively to arrival shocks upon impact for all four cities, with this negative effect persisting for Chennai and Mumbai. However, for Delhi and Kolkata, the negative response becomes insignificant after the first month. Additionally, we find that in

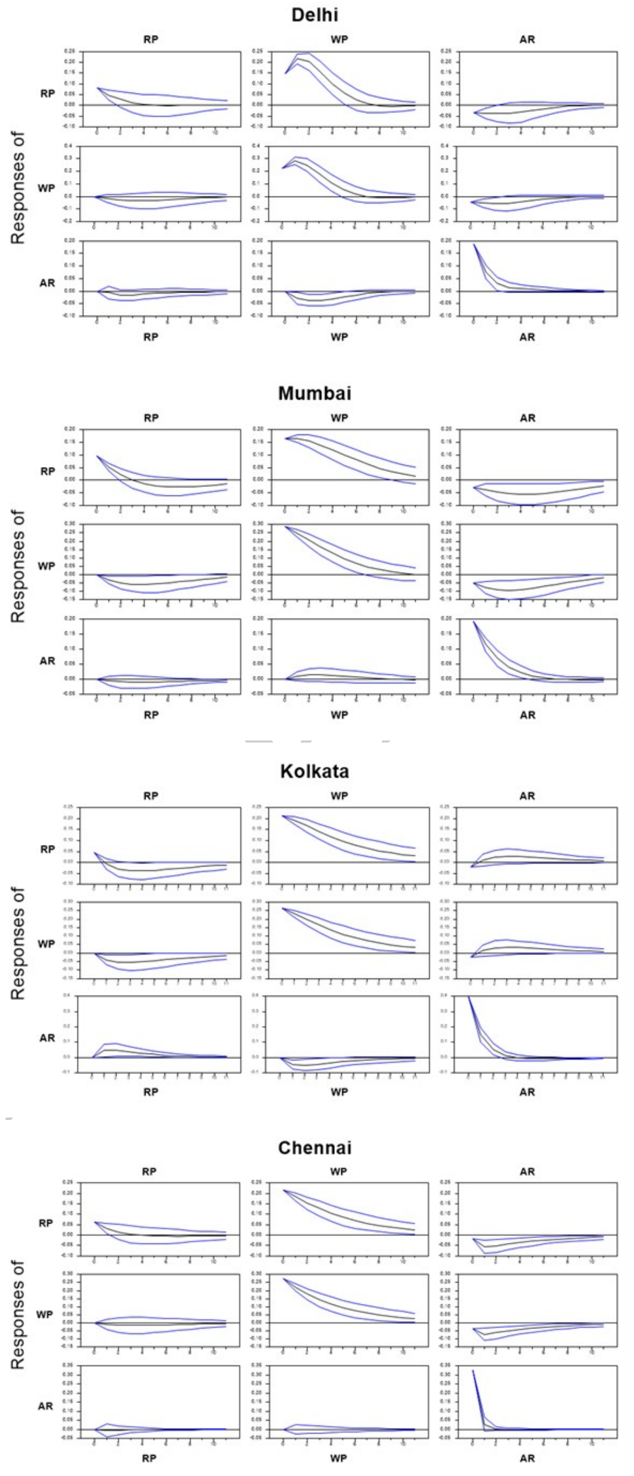

Figure 6. Impulse Response Analysis of Retail, Wholesale Prices, and Arrivals of Onions

Notes: The horizontal axis denotes the chosen time horizon; in this case, 12 months, starting from the initial period (0) stretching to 11 months into the horizon. The black line is the response function, whereas the associated blue lines are the 90% confidence intervals. The vertical axis measures the impact of the shock on the variables. To this end, RP, WP, and AR stand for retail price, wholesale price, and arrivals, respectively.

Table 5. Forecast from the VAR Model (In-Sample) Without Rainfall Deviations

	Delhi		Mumbai		Kolkata		Chennai	
	Actual	Forecast	Actual	Forecast	Actual	Forecast	Actual	Forecast
$f\_P_t^R$	3.50	3.25	3.57	3.02	3.59	3.15	3.36	3.00
% (−/+)	-22.12		-42.30		-27.91		-30.32	
$f\_P_t^W$	2.82	2.32	2.94	2.28	3.37	2.81	3.01	2.60
% (−/+)	-39.34		-48.31		-42.87		-33.63	
f_A_t	9.77	10.04	9.93	10.15	8.14	8.34	9.11	9.46
% (−/+)	+30.99		+24.61		+22.14		+41.91	

Notes: The notations $f\_P_t^R$, $f\_P_t^W$, and f_A_t denote the mean values (in logarithms) over the out-of-sample forecast period for retail, wholesale, and arrivals, respectively. The notation % (- / +) denotes the actual percentage increase or decrease in prices (Rupees per kilogram) and arrivals (in metric tonnes) if there were no rainfall anomalies and if we took the average rainfall anomalies over the last 26 months.

all cities, wholesale prices do not tend to respond to retail price shocks. Conversely, retail prices significantly respond to wholesale price shocks.[8]

Since we find evidence that rainfall anomalies do influence both wholesale and retail prices of onions as well as available supplies, it may be inferred that the agents partly change their behaviors to adapt to the weather anomalies. We test for this by conducting the same procedure in the spirit of Eckstein and Tsiddon (2004) but this time generate in-sample forecasts for the period March 2020 to April 2022 while using the data from March 2010 to February 2022. We then compare our forecasts with the actual data and in the same manner as before compute the percentage differences. The results are shown in Table 5 below.

Table 5 provides the actual data on retail and wholesale prices along with arrivals along with the forecasted data over the reference period. Assuming no rainfall deviations, the VAR-X reduces to a simple VAR. In the case of each city, the actual arrivals data is lower than the forecasts made from the VAR if rainfall deviations were not taken into account. This implies it would be expected that arrivals will be higher without rainfall deviations. Because the actual data on arrivals are lower, it means that agents are pessimistic about the conditions due to anomalies in rainfall and given the poor storage, allow for the forecasted arrivals to be higher in the *mandis*. For all the cities we see both retail and wholesale prices are forecasted to be lower if agents did not take rainfall deviations into account. The fact that actual prices are higher than the forecasted prices shows that agents take into account the rainfall anomalies, expecting the prices to be lower. For arrivals there is considerable variation, where it is lowest in Kolkata and almost twice that in Chennai. A similar variation is found in retail and wholesale prices where the difference between actual and forecasted prices could range between 21% to 48%.

Robustness

In this section we conduct a robustness test where we create a standardized rainfall deviation measure.[9] The extreme weather conditions in states that produce more onions should be given higher weights rather than equal weights. Accordingly, we collect data on onion production in the major states which is available on an annual frequency. We then calculate the share of each state and normalize the weights. These weights are placed on the rainfall deviations across the monthly data, where the weights are fixed for all months in each year, but vary year-on-year. Figure 7 shows the plot of standardized rainfall deviations.

[8] Further innovation accounting is carried out by conducting the forecast error variance decomposition analysis (see Table A.6 in the Appendix and the associated discussion on possible exogeneity) as well as the historical decomposition analysis (see Figure A.3 in the Appendix and the associated discussion).

[9] We thank an anonymous referee for raising this insightful comment

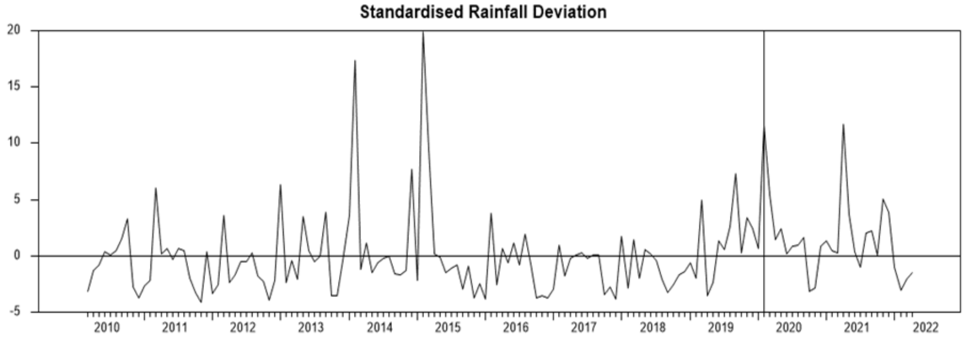

Figure 7. Standardised Rainfall Deviation

Notes: The source of the data is the Indian Meteorological Department (IMD) from where we obtain monthly rainfall deviation computed as the normal rainfall (which is set by the IMD) subtracted from actual rainfall for each individual onion producing state. We compute standardized rainfall deviation data as shown in the figure by attaching weights for each state based on the amount of onion produced in a year and normalizing the weights. The numbers on the vertical axis measure the percentage deviations and on the horizontal axis we plot the time span in monthly frequency from March 2010 to April 2022.

Table 6. Forecast from the VAR-X Model with Standardized Rainfall Deviation

	Delhi		Mumbai		Kolkata		Chennai	
	No RD	With RD	No RD	With RD	No RD	With RD	No RD	With RD
$fi\_P_t^R$	3.25	3.30	3.17	3.27	3.17	3.25	3.00	3.11
% (−/+)	+5.13		+10.51		+8.32		+11.63	
$fi\_P_t^W$	2.39	2.44	2.52	2.63	2.84	2.93	2.62	2.75
% (−/+)	+5.12		+10.41		+9.41		+13.88	
fi_A_t	10.01	10.00	10.10	10.07	8.32	8.32	9.41	9.38
% (−/+)	-0.99		-2.95		0.00		-2.95	

Notes: The notations $fi\_P_t^R$, $fi\_P_t^W$, and fi_A_t denote the mean values over the out-of-sample forecast period for retail, wholesale, and arrivals, respectively, for the forecast period i, where i = 1 ('No RD') or i = 2 ('With RD'). The column headings 'No RD' and 'With RD' show the forecast results over the counterfactual 'no rainfall deviation' scenario and standardized 'with rainfall deviation,' respectively. The notation % (- / +) denotes the actual percentage increase or decrease in prices (Rupees per kilogram) and arrivals (in metric tonnes) if there were no rainfall anomalies and if we took the average standardized rainfall anomalies over the last 26 months under column headings 'No RD' and 'With RD,' respectively.

We re-run the model using the procedure in the spirit of Eckstein and Tsiddon (2004). As before, we assume the counterfactual there is no rainfall deviation (R_j) starting from May 2022 and generate the forecasts over a 26-month (out-of-sample) period up to June 2024. We then allow rainfall deviation from May 2022 to June 2024 and we generate the forecasts over this period. After taking the differences of the two scenarios (no rainfall deviations and with rainfall deviations) we obtain the results shown in Table 6 below.

Table 6 can be compared against the results of Table 4. The estimates show the same expected signs, and therefore in terms of direction of prices and arrivals over the reference period of erratic rainfall, our results are consistent. However, we find using the standardized rainfall data, the magnitudes of the impact on retail and wholesale prices, along with arrivals are smaller in magnitude when compared to the results where we use non-standardized rainfall. For Kolkata the results are not too different, however, there is a significant drop in the magnitude of impacts for Chennai, Delhi and Mumbai. But, there is still an impact on prices that can either range from about 6% to 14% using standardized rainfall, or 9% to just under 20% using the non-standardized average rainfall anomaly data. Since, with standardized rainfall the anomalies are more erratic with a couple of significant spikes that precede the reference period, and relatively less pronounced spikes that follow, albeit

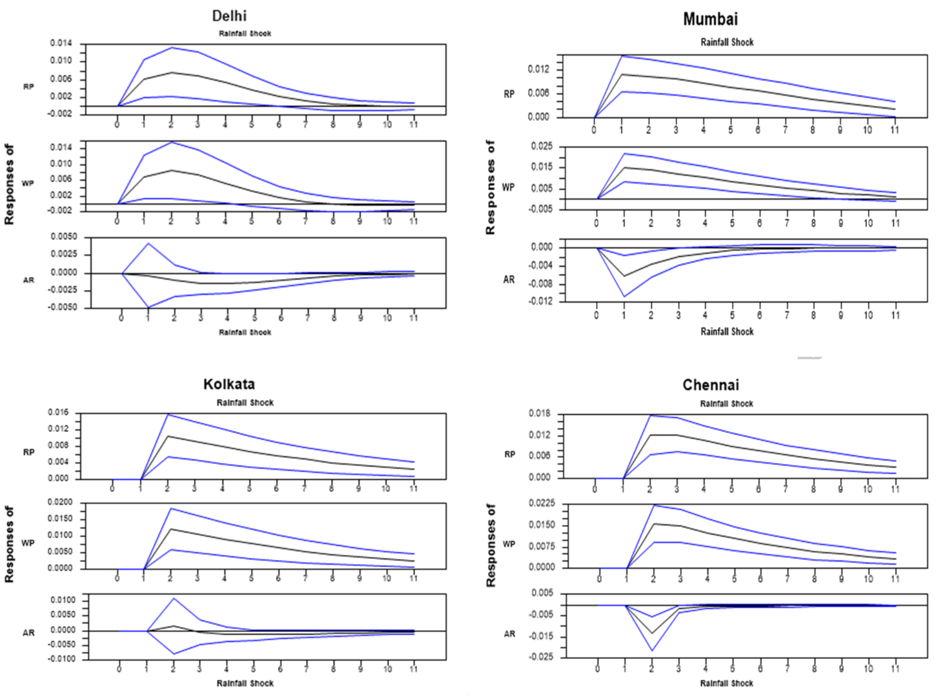

Figure 8. Impulse Response Analysis of Retail and Wholesale Prices and Arrivals of Onions to a Rainfall (standardized) Shock

Notes: The responses are shown in black due to a unit shock in rainfall deviation. On the vertical axis we have the magnitude of the responses to these shocks. On the horizontal axis we have the time horizon chosen to be 11 months in the future. The associated 1 standard deviation confidence intervals are given by the lines in blue that allow us to determine the significance of the responses of prices and arrivals to the rainfall shock.

frequently, within the reference period, the relatively lower magnitudes of our parameter estimates are not entirely surprising.

The results of the impulse response analysis are shown in Figure 8 with standardized rainfall data. We find that the shape of the responses for all the variables for each of the different cities is strikingly similar, thereby lending support to our robustness tests. The only difference as expected, is the magnitude and in some cases the duration and significance of the response of the prices and arrivals of onions to rainfall shocks. For example, Mumbai and Chennai are broadly similar in every respect in terms of time path and duration. While the time path of responses is similar for Delhi, the confidence intervals are slightly wider, rendering the response of arrivals being borderline insignificant over the time horizon 3 to 6 months. For Kolkata, while the time path is similar, the tighter confidence intervals show a longer significant persistence over the chosen time horizon. However, in general, the response of the variables to rainfall shocks, lead to broadly the same conclusions, as shown by the shape of the impulse response functions.

It needs to be noted that the standardized rainfall data can have its own measurement errors due to the lack of required data. While it is true that states that produce more onions should be given higher weights, the production data for states are not available at monthly frequency. Therefore, we used available annual data thereby allowing for the normalized weights only to vary every year. It needs to be noted that the harvesting period occurs three times in a year and varies from year to year. The Rabi season (from April to June) generally contributes the most. The Kharif season (from October to December) and the late Kharif season (from January to March) produce the rest of the yearly production. This again, can vary from year to year and state to state. Since only annual data is

Table 7. Forecast from the VAR-X Model with Average Rainfall Deviation

	Delhi		Mumbai		Kolkata		Chennai	
	No RD	With RD	No RD	With RD	No RD	With RD	No RD	With RD
$fi\_P_t^W$	3.23	3.33	3.16	3.29	3.12	3.23	2.94	3.04
% (−/+)	+10.51%		+13.88%		+11.63%		+13.88%	
$f\_P_t^W$	2.34	2.44	2.35	2.49	2.33	2.46	2.34	2.49
% (−/+)	+10.51%		+15.62%		+13.88%		+16.18%	
f_A_t	10.02	10.00	10.10	10.07	8.31	8.31	9.43	9.35
% (−/+)	−1.98%		−2.95%		−0.99%		−7.68%	

Notes: The notations $fi\_P_t^W$, $f\_P_t^W$, and f_A_t denote the mean values over the out-of-sample forecast period for retail, wholesale, and arrivals, respectively, for the forecast period i, where $i = 1$ ('No RD') or $i = 2$ ('With RD'). The column headings 'No RD' and 'With RD' show the forecast results over the counterfactual 'no rainfall deviation' scenario and standardized 'with rainfall deviation,' respectively. The notation % $(-/+)$ denotes the actual percentage increase or decrease in prices (Rupees per kilogram) and arrivals (in metric tonnes) if there were no rainfall anomalies and if we took the average rainfall anomalies over the last 26 months under column headings 'No RD' and 'With RD,' respectively.

available on onion production that averages out the monthly variations, the standardized production will still have certain limitations.

In the spirit of the structural gravity model of trade due to Anderson and Van Wincoop (2003), it is possible that wholesale prices in onion producing states can impact retail prices of onions in the four major onion consuming cities. Therefore, if retailers in consuming states purchase directly from the wholesalers in onion producing centers, then the price of the latter becomes an important variable to consider in our VAR-X model. Accordingly, we choose the largest onion producing center, Lasalgaon, located in the district of Nasik in Maharashtra.[10] From Lasangaon, onions are supplied to all parts of the country, and therefore the prices from this center are likely to have a cascading effect on onion prices in other parts of India (Gulati, Wardhan, and Sharma, 2022). We collected time series data on wholesale prices of onions for this center for the same time period considered in this study from AgMarknet, Directorate of Marketing & Inspection (DMI), Ministry of Agriculture and Farmers Welfare, Government of India.[11] Using the model due to Eckstein and Tsiddon (2004) with and without average rainfall deviation we obtain the results shown in Table 7 below.

Comparing these results with Table 4, we find that there is hardly much change in the retail and wholesale prices for Delhi, though the arrivals are affected substantially, where we see a drop from around 12% to 2%. Since Delhi receives onion supplies from several other states as well, such as Madhya Pradesh, Rajasthan and Gujarat (see Gulati et al. 2022), there is some impact on arrivals. For Mumbai, Kolkata and Chennai where almost all of their onion supplies are from Maharashtra, we do not see any significant change in onion arrivals. For Mumbai and Chennai, the impact on retail and wholesale prices is slightly lower, whereas for Kolkata it is found to be slightly higher, probably due to the higher transport costs. In general, the price changes range between 10% to just over 16%, slightly lower in range compared to the results in Table 4.

We repeat the same exercise this time using the standardized deviation of rainfall and the results are shown in Table 8 below.

When comparing these results with Table 6, we find that the effect on prices and arrivals are broadly in the same direction. The only exception is Delhi where we find no change at all in the results; both the signs and the magnitudes of change are similar. Further, we find the change in arrivals is largely unaffected, except for Mumbai where it is relatively lower. The direction of

[10] Another major center is Pimpalgaon. We do not include this data due to brevity, as the results are strikingly similar to Lasangaon and do not add anything which is different. Since the results would lead to adding two new extra tables of results, we choose not to include the results for Pimpalgaon in this section. However, the results are available from the authors on request.

[11] The data are available at: https://agmarknet.gov.in/

Table 8. Forecast from the VAR-X Model with Standardized Rainfall Deviation

	Delhi		Mumbai		Kolkata		Chennai	
	No RD	With RD	No RD	With RD	No RD	With RD	No RD	With RD
$fi\_P_t^W$	3.25	3.30	3.18	3.26	3.13	3.22	2.96	3.04
% (−/+)	+5.13%		+8.32%		+9.41%		+8.33%	
$f\_P_t^W$	2.36	2.41	2.38	2.46	2.34	2.45	2.36	2.46
% (−/+)	+5.12%		+9.20%		+11.62%		+10.51%	
f_A_t	10.02	10.01	10.09	10.07	8.33	8.32	9.41	9.38
% (−/+)	−0.99%		−1.98%		−0.99%		−2.95%	

Notes: The notations $fi\_P_t^W$, $f\_P_t^W$, and f_A_t denote the mean values over the out-of-sample forecast period for retail, wholesale, and arrivals, respectively, for the forecast period i, where $i = 1$ ('No RD') or $i = 2$ ('With RD'). The column headings no RD and with RD show the forecast results over the counterfactual 'no rainfall deviation' scenario and standardized 'with rainfall deviation' respectively The notation % (−/+) denotes the actual percentage increase or decrease in prices (Rupees per kilogram) and arrivals (in metric tonnes) if there were no rainfall anomalies and if we took the average standardized rainfall anomalies over the last 26 months under column headings 'No RD' and 'with RD' respectively.

price changes are identical, and the magnitude similar except with Mumbai and Chennai showing a slightly smaller magnitude and Kolkata slightly higher. In general, the price changes range between 5% to just over 11%, slightly lower in range compared to the results in Table 6; but overall, with the additional estimations using standardized rainfall and onion producing centers instead of onion consuming cities, our results are broadly similar lending support to the robustness tests.

Conclusion

Our study uncovers that the effects of shocks on both retail and wholesale onion prices are transitory. This suggests that government interventions aimed at stabilizing onion prices tend to counteract and mitigate any shocks to onion prices, making the effect of such shocks temporary in nature. The causality of onion prices with arrivals, varies among individual cities. We find that arrivals can have a mitigating effect on onion prices, although the extent of this effect may differ across cities. For instance, except for Delhi, we observe causality from arrivals to at least wholesale onion prices, if not retail prices, in the case of Mumbai, Kolkata, and Chennai. These arrivals encompass both harvests (which occur at least twice a year during the rabi and kharif seasons) and destocking. However, poor storage conditions in India lead to spoilage and shrinkage of onions. The inadequate storage facilities and high rent for existing cold storage prompt wholesalers to sell a significant portion of their onion arrivals to retailers, leaving limited quantities for storage. This dynamic explains the causal relationship between arrivals and prices. The discrepancy between production and storage growth rates underscores the need to make storage more accessible and affordable. Onion production predominantly occurs in the western, followed by the southern and northern regions of India. Kolkata being in the eastern region is likely to expect onion prices to be influenced by higher transportation costs compared to Mumbai, Delhi, and Chennai. Expanding onion cultivation in states such as Bihar, Odisha, and Assam could help meet the demand in eastern and north-eastern India. The distance from the production center, coupled with higher variability in onion arrivals, may contribute to the transmission of price and quantity signals in Kolkata.

In Chennai, Kolkata, and Mumbai (but not Delhi), we find arrivals affect wholesale prices. If traders opt to restrict the influx of onions into the market, prices could rise accordingly. This observation holds true for the cities we studied, except for Delhi, which has the lowest variability in onion arrivals compared to the other cities. More consistent arrivals (supply) leave less room for price manipulation by traders. Additionally, we find that prices cause changes in onion arrivals in the case of Kolkata, indicating that wholesalers adjust their storage and market release decisions based on price signals. Our findings suggest that, given Kolkata's distance from major onion-producing regions and inadequate storage facilities, wholesalers must swiftly interpret price and arrival signals to make informed decisions. We also observe different responses when comparing how retail and wholesale prices react to shocks in each other's prices in different cities. Finally, we find that rainfall anomalies have significant positive effects on onion prices and negative effects on arrivals. We find evidence that agents within the supply chain change their expectations to adapt to weather anomalies. Therefore, providing advance weather information along with crop insurance facilities to farmers can prove useful in helping them make informed planting decisions and protection against price variability, risk and uncertainty.

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A1. Onion Production, Exports and Imports in India

Table A1. Onion Production, Exports and Imports in India (million metric tonnes)

Year	Production	Exports	Imports
2010-11	15.12	1.18	0.0125
2011-12	17.51	1.31	0.0000128
2012-13	16.81	1.67	0.00045
2013-14	19.40	1.48	0.017843
2014-15	18.93	1.24	0.000387
2015-16	20.93	1.38	0.087324
2016-17	22.43	2.42	0.000087
2017-18	23.26	1.59	0.006593
2018-19	22.82	2.18	0.007081
2019-20	26.09	1.15	0.141189
2020-21	26.64	1.59	0.066264
2021-22	31.68	1.54	0.028512
2022-23	30.21	2.53	0.0
2023-24	24.12	1.61	0.020516

Notes: Data are collected from various sources: https://pib.gov.in/PressReleasePage.aspx?PRID=2042765 Agricultural and Processed Food Products Export Development Authority (APEDA), Ministry of Commerce & Industry, Govt. of India. https://agriexchange.apeda.gov.in/; 'Agricultural Statistics at a Glance' (2022) : published by the Economics & Statistics Division, Ministry of Agriculture & Farmers Welfare, Government of India.

A2. Seasonal Unit Root Tests

Hylleberg et al. (1990) (hereafter HEGY) proposed a test for the determination of unit roots at each of the seasonal frequencies ($\frac{\pi}{6}$, $\frac{\pi}{3}$, $\frac{\pi}{2}$, $\frac{2\pi}{3}$, $\frac{5\pi}{6}$, and π) individually or collectively. To save space, we only report the individual cases, but the joint results can be made available on request. The HEGY test can accommodate various deterministic specifications in the form of seasonal dummies, constants, and trends; we make use of the seasonal dummies as suggested by Osborn (1990). Moreover, we augmented the HEGY test with lags of the dependent variable chosen according to the AIC as additional regressors to the principal equation presented above, in order to mitigate the effect of serial correlation. See Hylleberg et al. (1990) for details.

The results of the seasonal unit root test are given below in Table A1. In each of the frequencies, we can see that the test statistic is greater in absolute terms than the computed critical values (approximately 0.73 at all seasonal frequencies, and −2.53 at the π frequency), and we can therefore reject the null hypothesis of a unit root in each of the variables (retail and wholesale prices, along with arrivals).

Table A2. Seasonal unit root tests (M-HEGY)

	$\frac{\pi}{6}$	$\frac{\pi}{3}$	$\frac{\pi}{2}$	$\frac{2\pi}{3}$	$\frac{5\pi}{6}$	π
Delhi P_t^R	0.66^a	0.09^a	0.53	0.24^a	0.07	0.02^b
Delhi P_t^W	−0.13	0.03	1.36	-0.48^a	0.05	0.02
Delhi A_t	−0.08	−0.10	−0.07	0.06	0.40^a	−0.01
Mumbai P_t^R	0.58^a	0.09^a	0.86	0.25	0.07	0.02
Mumbai P_t^W	-0.28^b	-0.18^c	1.62	0.94	0.09	0.02^b
Mumbai A_t	−0.05	0.64^a	−0.96	0.39	-0.11^b	0.03^b
Kolkata P_t^R	−0.13	0.02	0.25	0.02	0.02^b	-0.01^a
Kolkata P_t^W	−0.87	0.02	0.94	0.39	0.02^b	-0.01^a
Kolkata A_t	0.99	0.01	0.39	0.39	0.03^b	0.02
Chennai P_t^R	0.54^a	-0.11^b	0.02^b	−0.13	-0.12^c	0.02^b
Chennai P_t^W	−0.13	-0.12^c	0.03^b	−0.13	0.02^b	−0.02
Chennai A_t	−0.07	1.07	-0.01^a	−0.07	0.02^b	−0.02

Notes: The 10% significance levels are obtained using linear interpolation and are approximately 0.73 at all seasonal frequencies, and −2.53 at the π frequency. The rejection of the unit root null for this particular variable at this particular frequency π using the HEGY test on monthly frequencies appears to be an anomaly as it is close to the critical value of −2.53 at the 10% significance level. While for this variable we do not reject the null of no unit root at this particular frequency π, using the Canova-Hansen test we cannot reject the null hypothesis of no unit root at this specified frequency (we can report test statistic 0.34 which is less in absolute value than 0.35 at 10% and 0.47 at 5% significance levels respectively).

A3. Unit root tests allowing for non-stationary volatility

We employ the test proposed by Smeekes and Taylor (2012), which is a bootstrap union test for unit roots in the presence of non-stationary volatility. This test builds on the procedure by Harvey, Leybourne, and Taylor (2012) dealing with the uncertainty about the trend and the initial condition. Smeekes and Taylor (2012) extend the work of Harvey, Leybourne, and Taylor (2012) by allowing for the possible presence of nonstationary volatility. This is done by considering union tests that are robust to nonstationary volatility, trend uncertainty, and uncertainty about the initial condition. To this end, they consider two bootstrap union tests, 'unit root A type' test, denoted UR_{4A} and 'unit root B type' test, denoted UR_{4B}; the former test, that is UR_{4A} does not include a deterministic trend in the test, while the latter, that is, UR_{4B} does include a trend in the bootstrap data generating process. The results of this test are shown in Table A2 below. In each of the variables we can see that the estimated UR-statistic is greater than the bootstrapped critical values and therefore we can reject the unit root null allowing for nonstationary volatility.

Table A3. Unit Root Tests Allowing for Non-stationary Volatility

	UR-statistic	Bootstrapped critical value	
		UR_A [p-value]	UR_B [p-value]
Delhi P_t^R	−4.138	−2.011 [0.00]	−2.011 [0.00]
Delhi P_t^W	−4.772	−2.092 [0.00]	−2.091 [0.00]
Delhi A_t	−6.695	−2.022 [0.00]	−2.063 [0.00]
Mumbai P_t^R	−3.842	−2.103 [0.00]	−2.103 [0.00]
Mumbai P_t^W	−4.871	−2.056 [0.00]	−2.060 [0.00]
Mumbai A_t	−3.739	−2.148 [0.00]	−2.145 [0.00]
Kolkata P_t^R	−3.882	−2.066 [0.00]	−2.055 [0.00]
Kolkata P_t^W	−4.391	−2.096 [0.00]	−2.095 [0.00]
Kolkata A_t	−6.604	−2.305 [0.00]	−2.305 [0.00]
Chennai P_t^R	−4.326	−2.069 [0.00]	−2.058 [0.00]
Chennai P_t^W	−4.328	−2.025 [0.00]	−2.025 [0.00]
Chennai A_t	−10.40	−2.076 [0.00]	−2.076 [0.00]

Notes: Numbers in square brackets denote p − values.

Table A4. Estimates of the VAR-X Model

	Delhi			Mumbai			Kolkata			Chennai		
	P_t^R	P_t^W	A_t	P_t^R	P_t^W	A_t	P_t^R	P_t^W	A_t	P_t^R	P_t^W	A_t
P_{t-1}^R	0.66^a	−0.13	−0.08	0.58^a	-0.28^b	−0.05	−0.13	−0.87	0.99	0.54^a	−0.13	−0.07
P_{t-2}^R	0.09^a	0.03	−0.10	–	–	–	–	–	–	–	–	–
P_{t-1}^W	0.53	1.36	−0.07	0.24^a	1.05^a	0.06	0.86	1.62	−0.96	0.25	0.94	0.05
P_{t-2}^W	−0.45	-0.48^a	0.12	–	–	–	–	–	–	–	–	–
A_{t-1}	0.07	0.05	0.40^a	−0.06	-0.18^c	0.64^a	0.07	0.09	0.39	-0.11^b	-0.12^c	1.07
A_{t-2}	−0.04	−0.08	0.01	–	–	–	–	–	–	–	–	–
RD_{t-i}	0.02^b	0.02	−0.01	0.03^b	0.04^b	−0.02	0.02	0.02	0.01	0.02^b	0.03^b	-0.01^a

Notes: The superscripts a, b and c denote rejection of the null hypothesis of no significance at the 1%, 5% and 10% significance levels respectively. The lag lengths for the associated rainfall deviation chosen according to the SBC are 1 for Delhi and Mumbai and 2 for Kolkata and Chennai.

A4. Diagnostic Serial Correlation

To test for serial correlation in the VAR-X model, we make use of the Edgeworth expansion corrected likelihood ratio statistic as well as the Rao F-test version of the LM statistic. In Table A5 below, we find that in all cases when estimating the VAR-X model for the four cities, Delhi, Mumbai, Kolkata, and Chennai, the null hypothesis of no serial correlation cannot be rejected.

Table A5. Diagnostics of the VAR-X Model

	LM test for serial correlation			
	LRE-stat	p-value	Rao F-stat	p-value
Kolkata	11.17	0.26	1.25	0.26
Delhi	11.65	0.23	1.30	0.23
Mumbai	2.74	0.97	0.303	0.97
Chennai	13.41	0.14	1.51	0.14

Notes: We do not conduct Ljung-Box Q tests as the p-values may not be reliable with exogenous variables.

A5. Variance Error Decomposition Analysis

Using the VAR model in (4) and setting $z_t = [(P_t^R, P_t^W, A_t)']$ to be the vector of endogenous variables comprising retail prices, wholesale prices, and availability of onions, we can obtain the j-step ahead forecast as shown in (10):

$$E_T(z_{T+j}) = A_0[I + A_1 + A_1^2 + \cdots + A_1^{(j-1)}] + A_1^j z_T$$

We can work out the associated forecast error (given by e_t) as:

$$e_{(t+j)} = A_1 e_{(t+j-1)} + A_1^2 e_{(t+j-2)} + \cdots + A_1^{(j-1)} e_{(t+1)}$$

As with the impulse response analysis, it is possible to write these forecast errors in terms of the structural errors η_t^R, η_t^W, and η_t^A. The forecast error decomposition informs us of the proportion of the movements in a data series due to its own shocks versus the shocks to other variables. For example, we can obtain the proportion of movements in the retail price series due to shocks in η_t^R versus the shocks to η_t^W and η_t^A.

If η_t^R shocks explain none of the forecast error variance of P_t^W at a sufficiently long horizon, then we can say that the P_t^W series is exogenous. In this sort of situation, the P_t^W series evolves independently of the η_t^R shock and the P_t^R data series. At the other extreme, if η_t^R shocks explain all of the forecast error variance of P_t^W at a sufficiently long horizon, then we can say that the P_t^W series is endogenous.

However, as we see from the results in Table 5A below, we find that for P_t^R and A_t almost all of its forecast error variance is explained at short horizons and smaller proportions at longer horizons. For the P_t^W series, however, more of the forecast error variance is explained at longer horizons for Delhi and Mumbai, whereas in Kolkata and Chennai the proportion explained is lower and gradually increasing. However, the results show no signs of being entirely exogenous nor endogenous in any of the cities, validating our VAR model setup.

Table A6. Forecast Error Variance Decomposition Analysis

Panel A: Delhi

Horizon	On Retail			On Wholesale			On Arrivals		
	P_t^R	P_t^W	A_t	P_t^R	P_t^W	A_t	P_t^R	P_t^W	A_t
1	100.00	0.000	0.000	78.657	21.342	0.000	1.327	4.811	93.861
2	90.988	9.006	0.005	69.048	30.908	0.042	3.231	7.1696	89.598
3	78.302	21.370	0.327	60.151	39.729	0.118	3.196	9.342	87.461
4	70.979	28.754	0.266	57.176	42.600	0.222	3.465	13.891	82.643
5	66.201	33.272	0.525	52.718	47.037	0.243	3.270	21.753	74.976
6	64.903	34.346	0.750	50.345	49.402	0.251	3.276	22.464	74.259
7	64.736	34.487	0.775	50.152	49.177	0.669	4.717	21.902	73.380
8	64.918	34.304	0.776	50.134	48.428	1.436	5.975	21.421	72.603
9	64.876	34.188	0.934	49.820	47.393	2.785	9.108	24.728	66.163
10	64.743	34.262	0.994	50.132	46.812	3.054	8.909	28.127	62.962
11	64.751	34.176	1.071	50.205	46.569	3.2246	8.830	28.314	62.855
12	64.427	34.139	1.433	49.660	46.373	3.9658	9.969	27.181	62.849

For Mumbai

Horizon	On Retail			On Wholesale			On Arrivals		
	P_t^R	P_t^W	A_t	P_t^R	P_t^W	A_t	P_t^R	P_t^W	A_t
1	100.00	0.000	0.000	75.170	24.829	0.000	2.356	0.300	97.343
2	98.118	1.877	0.004	70.326	29.306	0.367	1.985	0.236	97.778
3	94.994	4.938	0.067	66.144	32.824	1.031	1.806	0.407	97.786
4	91.529	8.225	0.244	62.714	35.459	1.825	1.740	0.703	97.556
5	88.245	11.218	0.536	60.025	37.344	2.629	1.724	1.020	97.255
6	85.399	13.693	0.906	58.007	38.628	3.363	1.723	1.293	96.983
7	83.086	15.604	1.309	56.561	39.454	3.984	1.723	1.496	96.780
8	81.304	16.995	1.700	55.577	39.948	4.474	1.721	1.631	96.646
9	79.997	17.953	2.048	54.943	40.218	4.838	1.720	1.713	96.566
10	79.084	18.577	2.337	54.561	40.346	5.092	1.720	1.757	96.522
11	78.477	18.960	2.561	54.348	40.392	5.259	1.722	1.778	96.499
12	78.095	19.178	2.725	54.241	40.397	5.361	1.725	1.786	96.487

For Kolkata

Horizon	On Retail			On Wholesale			On Arrivals		
	P_t^R	P_t^W	A_t	P_t^R	P_t^W	A_t	P_t^R	P_t^W	A_t
1	100.00	0.000	0.000	64.467	35.532	0.000	1.392	0.081	98.526
2	96.666	3.208	0.124	70.468	29.162	0.369	2.029	3.733	94.237
3	93.784	4.579	1.636	71.960	27.503	0.535	3.332	6.780	89.887
4	90.627	4.456	4.915	71.737	26.158	2.104	4.496	8.707	86.795
5	87.514	4.078	8.406	70.754	25.088	4.156	5.125	9.712	85.162
6	84.739	4.105	11.154	69.636	24.532	5.830	5.340	10.12	84.536
7	82.572	4.607	12.820	68.743	24.446	6.810	5.371	10.245	84.382
8	81.092	5.317	13.590	68.174	24.606	7.218	5.369	10.267	84.363
9	80.195	5.960	13.843	67.866	24.810	7.322	5.383	10.265	84.350
10	79.706	6.410	13.883	67.716	24.960	7.322	5.409	10.263	84.327
11	79.464	6.667	13.868	67.649	25.040	7.309	5.432	10.262	84.305
12	79.356	6.780	13.853	67.621	25.073	7.304	5.446	10.261	84.292

For Chennai

Horizon	On Retail			On Wholesale			On Arrivals		
	P_t^R	P_t^W	A_t	P_t^R	P_t^W	A_t	P_t^R	P_t^W	A_t
1	100.00	0.000	0.000	90.288	9.711	0.000	1.494	2.878	95.626
2	98.479	0.619	0.901	90.940	8.365	0.694	1.596	2.874	95.529
3	98.294	0.837	0.868	91.802	7.604	0.592	1.578	2.835	95.585
4	98.308	0.874	0.817	92.279	7.186	0.533	1.589	2.837	95.572
5	98.361	0.858	0.779	92.511	6.980	0.507	1.633	2.835	95.531
6	98.392	0.843	0.764	92.602	6.896	0.501	1.676	2.834	95.488
7	98.402	0.838	0.759	92.627	6.870	0.502	1.709	2.833	95.456
8	98.400	0.840	0.758	92.630	6.865	0.504	1.728	2.833	95.438
9	98.397	0.844	0.758	92.628	6.865	0.505	1.738	2.833	95.428
10	98.394	0.847	0.758	92.626	6.867	0.506	1.742	2.832	95.424
11	98.392	0.848	0.758	92.625	6.867	0.506	1.743	2.832	95.423
12	98.391	0.849	0.758	92.625	6.868	0.506	1.744	2.832	95.423

A6. Variance Profile Plot

Since onion prices appear to be volatile, to establish the presence of non-stationary volatility we follow the procedure by Cavaliere and Taylor (2007). They construct a variance profile $\hat{\eta}_s$ which is determined by:

$$\hat{\eta}_s = \frac{\sum_{t=1}^{\lfloor sT \rfloor} \hat{v}_t^2 + (sT - \lfloor sT \rfloor)\hat{v}_{\lfloor sT \rfloor+1}^2}{\sum_{t=1}^{T} \hat{v}_t^2}$$

where $\hat{v}_t$ is the estimated residual of the error term of the price/availability trend on its own lag (we regress the price/availability of onions on a constant and a linear trend). The variance profile measures unconditional volatility often referred to as nonstationary volatility. The method produces a graph to determine whether the variance is constant or not. The graphs for each variable are shown in Figure A1 below.

The first and second column of graphs show the variance profile plots of the retail and wholesale prices for the four cities. So, in the first column panels (A), (D), (G) and (J) are retail prices and panels (B), (E) (H) and (K) are wholesale prices for the Mumbai, Delhi, Chennai and Kolkata respectively. The graphs show that the variance is constant for the retail and wholesale prices for the four cities. This is deduced by the fact that the variance plot is closely aligned with the 45-degree diagonal. In the last column which shows the variance profile for arrivals, the variance shows signs of volatility except for Delhi given by panel (F) and to some extent Mumbai (panel C). However, the nonstationary volatility for any of the prices or arrivals data is not an issue given the unit root test results we obtain from table A3 that accounts for possibly non-stationary volatility.

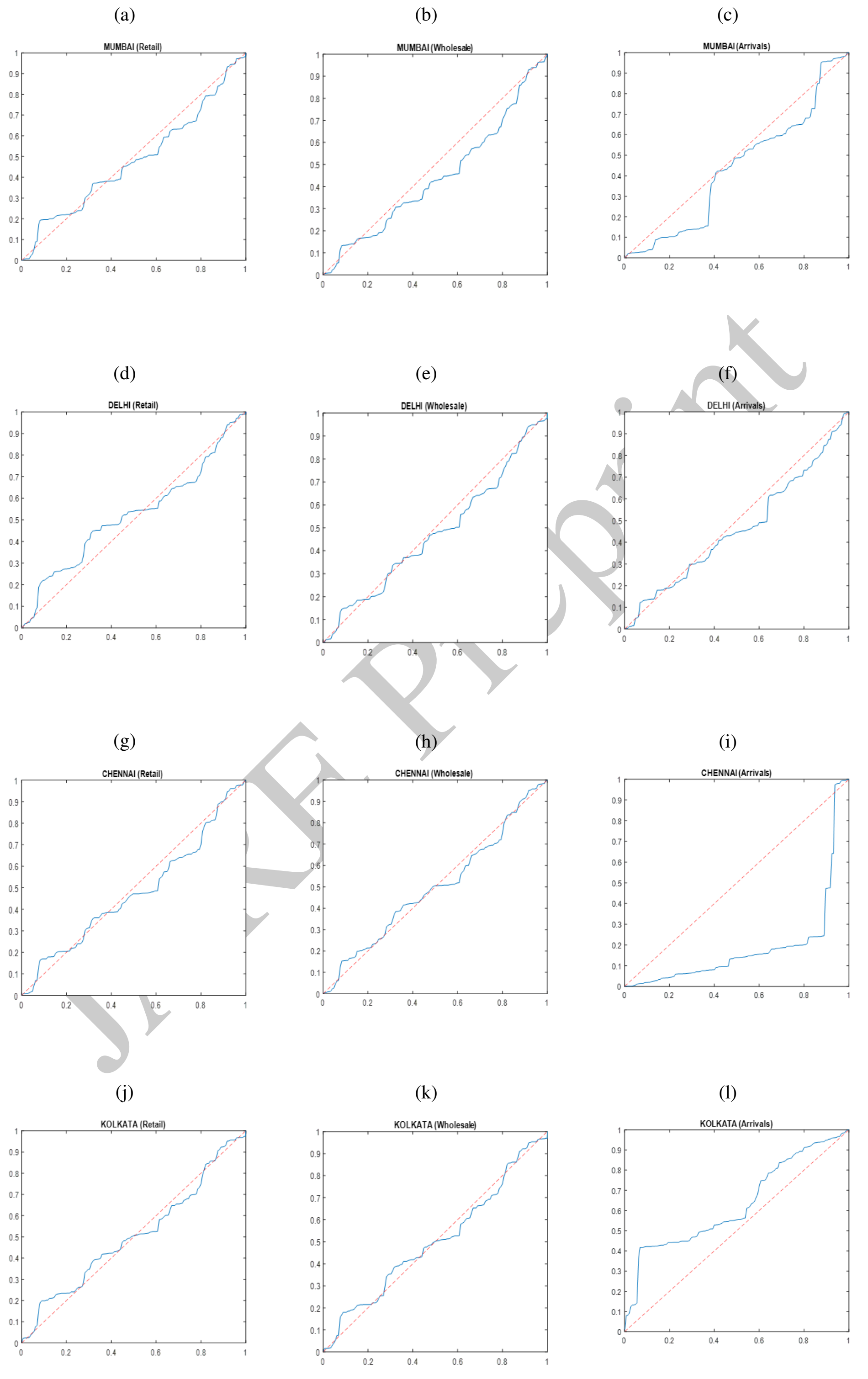

Figure A1. Variance Profile of logged prices (retail and wholesale) and arrivals

A7. Roots of the characteristic polynomial in the complex unit circle

We can conclude about the order of integration of the variables in the vector $\mathbf{x}_t = [P_t^R, P_t^W, A_t]'$ by showing that the VAR model in Eq. (4) is stable. Writing out the VAR model, we have:

$$\mathbf{x}_t = A_1\mathbf{x}_{t-1} + A_2\mathbf{x}_{t-2} + A_3\mathbf{x}_{t-3} + \cdots + A_p\mathbf{x}_{t-p} + \boldsymbol{\epsilon}_t$$

Using the lag operator, the above process can be written as:

$$(I - A_1L - A_2L^2 - \cdots - A_pL^p)\mathbf{x}_t = \boldsymbol{\epsilon}_t$$

The VAR model is stable if $|A(z)| = \det(I - A_1z - A_2z^2 - \cdots - A_pz^p) \neq 0; |z| < 1$.

Alternatively, $\mathbf{x}_t$ is stable if all the roots of the determinantal polynomial lie outside the unit root circle, in which case $\mathbf{x}_t \sim I(0)$. Since we are using lag operators, the inverse of the characteristic roots will mean that the roots must lie inside the complex unit root circle for stability. Below, in Figure A2, we plot the eigenvalues (characteristic roots) of the determinantal polynomial on the complex unit root circle. As we can see, they all lie within the circle, implying that the variables are indeed stationary $I(0)$ processes.

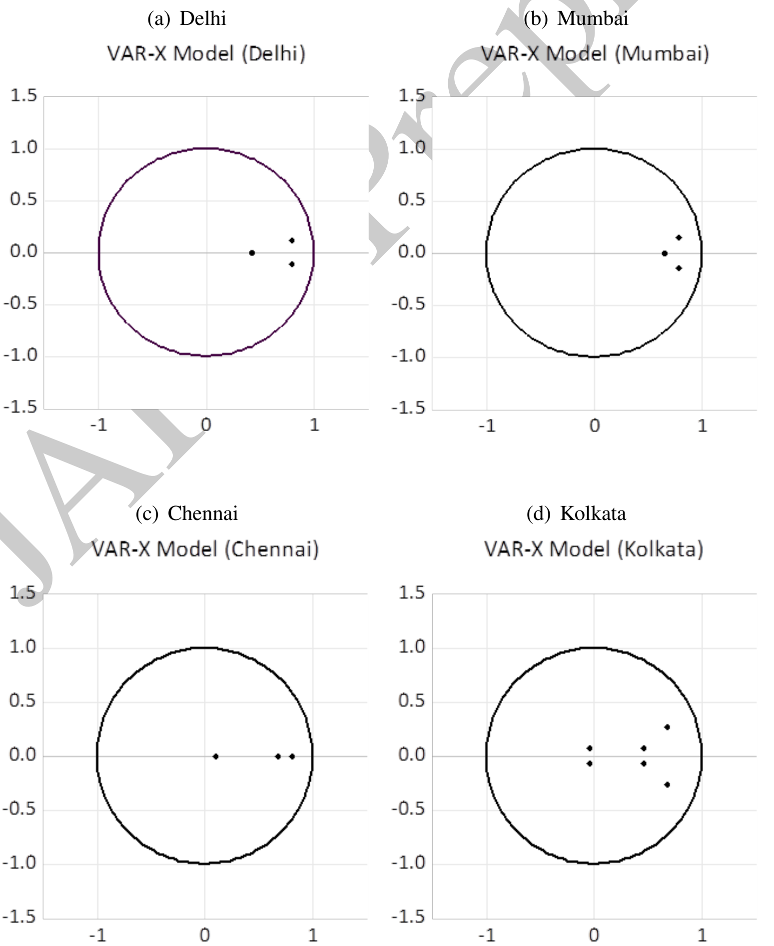

Figure A2. Plot of eigenvalues of characteristic polynomial in the unit circle for different cities

A8. Historical Decompositions

In Figure A3, panels A to D, we trace out the cumulative contributions to each structural shock to the retail, wholesale price and availability of onions in Delhi, Mumbai, Kolkata and Chennai respectively. Each of the nine figures in each panel shows how retail prices, wholesale prices, and availabilities of onions respond to each of the structural shocks in the variables. In each case, the large fluctuations in both the retail and wholesale prices are mainly driven by all three shocks with relatively more effect on wholesale prices. In the case of arrivals, the retail and wholesale price shock effects are lower in comparison to the shock in arrivals of onions.

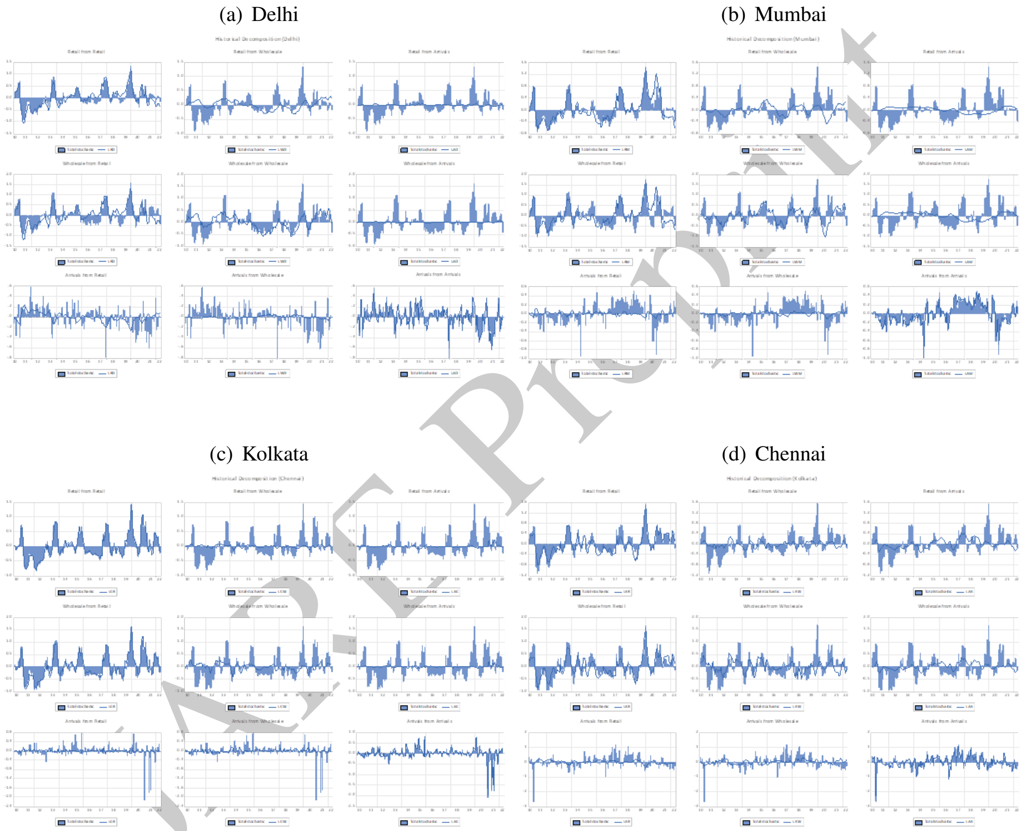

Figure A3. Historical Decomposition by City