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Market Analysis and Price Dynamics in Perishable Crop Supply Chains in India

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ABSTRACT

Applying a standard vector autoregressive model and the Granger causality test to long-ranging monthly price and market arrival data of a perishable crop (tomato) for eighteen major Indian cities, this paper examines the dynamics of price transmission across wholesale–retail supply chains of the crop, evaluating the interconnectedness between its market arrivals and wholesale and retail prices. Doing so, it tries to indicate the proximate reasons for the variability in tomato prices in the country. The prices and market arrivals of tomatoes are characterized as stationary series with substantial asymmetry and nonnormality in their distributions. The results show that while the retailers set their prices based on wholesale prices, the wholesalers were influenced by the price signals from retail markets in setting their prices and adjusting the quantity of tomatoes they released onto the market. While market arrivals of the crop influenced the prices in a majority of the cities, the prices also influenced market arrivals in several cases, indicating that variability in the availability of the crop contributed to the volatility in prices, which might have been intensified by the traders' market power, enabling them to control their availability in the markets. The policies to reduce price variability and enhance market integration and efficiency need to be directed towards ensuring regularity in the availability of the crop, facilitating trade, improving infrastructure facilities, and reducing restrictions on information sharing and movement of the commodity across markets.

Keywords: Vector autoregression, Granger causality, price volatility, market integration, supply chain

JEL Classification: C22, C32, O13, Q13

I

INTRODUCTION

Variability with frequent huge spikes in the prices of some perishable crops like tomato, onion, and potato (TOP) has been a major challenge to policymakers in India. The current market scenario of these crops is characterized by fragmented value chains, price volatility, post-harvest losses, and other market inefficiencies (Roy *et al*., 2024). These crops have relatively high price volatility relative to other crops, primarily due to their perishability and weather-sensitive and seasonal nature of production. The government launched a programme called 'Operation Greens' in 2018-19 for the integrated development of the TOP value chains, aiming at reducing price volatility, ensuring better value realization for farmers, and minimizing post-harvest losses. Among these crops, tomatoes as an important vegetable, holding a significant position in the Indian diets across different income groups and regions, are known for having the most volatile prices. The incredible spikes in tomato prices and the associated problems become newspaper headlines almost every year. For instance, in the first week of July 2024, the wholesale prices of tomatoes surged by more than 70 percent, and the retail prices almost doubled in a month in several metropolitan cities including Delhi, as output in major tomato-producing states such as Andhra Pradesh and Karnataka was adversely affected by virus infestation in

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summer crops due to high temperatures, and heavy rains disrupted supplies from some of the tomato-growing states (https://www.deccanherald.com/business/economy/tomato-prices-surge-to-over-rs-80-per-kg-3094632). A year back, tomato prices surged astronomically during the 2023 monsoon season; in contrast, tomatoes were previously sold at Rs. 15-20 per kilogram, the wholesale price touched an astounding Rs. 250 per kilogram and the retail price shot up over Rs. 350 per kilogram in some markets during July-August 2023. The prices eased after September, as fresh supplies arrived from southern and western states. Cyclonic storms and untimely excessive rainfall in some major tomato-growing states such as Karnataka, Andhra Pradesh, and Maharashtra, created havoc causing significant production losses and a substantial reduction in market arrivals, which contributed significantly to the sharp rise in prices (https://www.financialexpress.com/business/industry-tomato-price-crisis-solutions-to-alleviate-implications-on-indias-supply-chain-and-trade-operations-3239784/).

Tomato prices usually increase during July–August and then again in October–November due to lean production seasons in the major producing regions. The peak harvesting season occurs from December to February. Naturally, tomato prices usually remain at their highest level July to August and at their lowest level during December to March. This is a regular phenomenon, and the country witnesses such episodes of price crashes and peaks, very often, more than once in a year. Apart from the normal price seasonality due to production the seasonality and varying cycles of planting and harvesting seasons across regions, temporary supply chain disruptions and crop damage due to adverse weather conditions often lead to sudden price spikes. It is argued that the variations in tomato price volatility are mostly driven by supply-side factors (Gulati *et al*., 2022). Besides, the very nature of the crop which is a short duration (two to three months) and highly perishable, regional concentration of production and lack of adequate infrastructure facilities for storage and transportation largely account for the price volatility. An imperfect market structure and inefficient value chain often lead to volatility in prices, as the presence of a large number of intermediaries between the farmer and the consumer provides scope for earning huge marketing margins and inflating the prices.

Volatility in the prices disrupts the supply chains and affects the farmers, wholesalers, retailers, and consumers differentially with cascading effects on the trading operations of the crop. Supply shocks due to unpredictable weather cause wide fluctuations in production and market arrivals, affecting the prices and food security adversely. Unexpected and wide fluctuations in prices, distort farmers' production and investment decisions, leading to inefficient allocation of resources and unsteadiness in farm incomes (Lee and Park, 2013). Price volatility makes it difficult for the government to create an efficient supply chain to attain its dual goals of ensuring remunerative prices to farmers and the availability of the vegetables at affordable prices to consumers (Gulati *et al*., 2022). Volatility in prices also poses a food security risk to consumers, particularly to those who spend a large share of their income on food items (Hernandez *et al*., 2013). Controlling the price volatility and managing the risk from the price volatility of perishable agricultural commodities are matters of great concern to the policymakers to ensure steady farm incomes and the smooth functioning of the supply chains. Understanding the dynamics of price transmission between agents in the supply chain is important from a policy perspective. This understanding could improve the insights of policymakers regarding inflation dynamics and help them optimize supply chain management policies to increase market efficiency and minimize the impact of price spikes/volatility in the supply chain. This paper aims to contribute to this understanding by investigating tomato price transmission between wholesale and retail markets, taking into account the influence of market arrivals of the crop on price volatility.

The studies in the existing literature mostly evaluated spatial integration and price transmission across some arbitrarily selected tomato markets in India (see, for example, Kumar and Gajanana, 2022; Guleria *et al*., 2022; Shubham *et al*., 2024). Very few studies (viz., Padhi *et al*., 2023 and Sharma *et al*., 2024) addressed the issue of vertical integration in tomato markets. While Padhi *et al*. (2023) found evidence of unidirectional price transmission from wholesale to retail levels with no indication of asymmetric adjustments in prices, Sharma *et al*. (2024) reported evidence of short-run symmetry but long-run asymmetry in price adjustments in the wholesale–retail supply chain. Asymmetric adjustment in prices is interpreted as an indication of market imperfections and price inefficiency.

For evaluating tomato market integration, the past studies applied the maximum likelihood method of cointegration (Johansen 1988; Johansen and Juselius 1990) or standard autoregressive distributed lag (ARDL) and non-linear ARDL cointegration models (Pesaran and Shin, 1999; Pesaran *et al*., 2001; Shin *et al*., 2014), based on their observation that the prices are non-stationary. However, we shall see that the wholesale and retail prices and market arrivals of tomatoes are characterized as stationary I(0) processes and hence cointegration models are not applicable. A major gap in the existing literature is the lack of studies dealing with the dynamics of price transmission in the wholesale–retail supply chain, taking into account the impact of market arrivals on prices. Adequate attention was not given to identifying the possible reasons for tomato price variations over time.

Based on an alternate empirical methodology, applying a standard vector autoregressive (VAR) model and the Granger causality test to long-ranging monthly tomato prices and availability data for a set of objectively selected tomato markets representing different locations and market characteristics throughout the country, this paper evaluates the vertical integration of tomato markets, focusing on the dynamics of price transmission in the wholesale–retail supply chains in conjunction with the influence of market arrivals (availability) on prices. The price dynamics have been investigated for as many as eighteen major Indian cities, evaluating the interconnectedness between market arrivals and wholesale and retail prices of the crop. The paper explores the proximate reasons for the variability in tomato prices in the country.

The rest of the paper is organized as follows. Section 2 describes the dataset and evaluates the behaviour of wholesale and retail prices and market arrivals of tomatoes in the selected cities. Section 3 outlines the methodology. Section 4 investigates the dynamics of price transmission in the supply chain, taking into account the influence of market arrivals on prices. The concluding section states the implications of the results and draws policy conclusions.

II

DATA AND THEIR PROPERTIES

2.1 The Dataset

The study is based on the dataset comprising monthly wholesale and retail prices (Rupees per quintal) and market arrivals (metric tonnes) of tomatoes, reported in eighteen major cities (markets) in India (viz., Bhopal, Hyderabad, Bengaluru, Chennai, Ahmedabad, Bhubaneswar, Kolkata, Mumbai, Raipur and Patna; Chandigarh, Dehradun, Delhi, Jammu, Lucknow, Ranchi, Shimla, and Trivandrum) for the period from January 2010 to May 2024. The missing data for some variables at some time points were interpolated. Data for a few months during COVID-19 lockdown period were not reported for some markets. We have estimated trend lines for the variables with the available data and then used them to estimate the missing ones. We have considered a comprehensive list of tomato markets that represent different locations and market characteristics throughout the country. The first ten cities are located in major tomato-growing states, such as Madhya Pradesh (14 percent), Andhra Pradesh (11 percent), Karnataka (10 percent), Tamil Nadu (8 percent), Gujarat (7 percent), Odisha (7 percent), West Bengal (6 percent), Maharashtra (6 percent), Chhattisgarh (5 percent), and Bihar (5 percent) respectively, together producing about 80 percent of total tomato production in India (20.33 million metric tonnes) in 2021-22 (Government of India, 2023), and the remaining eight are located in minor producing or non-producing states/union territories, viz., Chandigarh (capital of Punjab and Haryana), Uttarakhand, Delhi, Jammu & Kashmir, Uttar Pradesh, Jharkhand, Himachal Pradesh, and Kerala, respectively. Hyderabad, which was the state capital of Andhra Pradesh, has become the state capital of Telangana since the state was formed on June 2, 2014. Telangana contributed 4.2 percent to total tomato production in the country in 2020-21. The dataset was compiled from the database of the National Horticulture Board (Ministry of Agriculture and Farmers Welfare, Government of India, New Delhi), available at (http://www.nhb.gov.in/OnlineClient/MonthwiseAnnualPriceandArrivalReport.aspx).

2.2 Trends in Tomato Prices and Market Arrivals

The nature of variability in the wholesale and retail prices and market arrivals of tomatoes for each of the selected cities (markets) can be seen in Figure A-1 to A-18 in the Appendix. The price and market arrival data are transformed into natural logarithms. The figures, presenting the logarithms of monthly price and market arrival data for the period under consideration, amply demonstrate the volatile nature of the prices, as they fluctuated within and between years. Both the prices fluctuated widely throughout a year with spikes at several time points in all the cities. Occasionally, the prices fall below the cost of production in the harvesting season and reach the peak during the lean season. The prices appear to have evolved similarly over time; the price pattern shows the co-movement of wholesale and retail prices in all the markets. The positive and statistically significant correlation coefficients between wholesale and retail prices support this observation (Table 1). This may be interpreted as providing suggestive evidence that the prices are integrated in the wholesale–retail supply chain.

However, the retail prices, appear to have been adjusted asymmetrically with the changing wholesale prices. A visual inspection of the data presented in the figures reveals that the price increases at the wholesale level were adjusted faster at the retail level than the price decreases. While the retail prices were adjusted promptly in proportion to the rising wholesale prices, they were not reduced in the same proportion as the declining wholesale prices. Asymmetric adjustment in prices is often interpreted as an indication of trader's market power, market imperfections, and price inefficiency (Sharma *et al*., 2024). The retailers seem to have enjoyed an advantage over the wholesalers presumably due to information asymmetry, high transaction costs, and inadequate storage facilities. Some markets appear to have persistently higher price markups than others. The traders seem to have earned relatively high marketing margins (the difference between retail and wholesale prices) at both high and low prices. This pattern did not change much even after the revisions to APMC laws and the adoption of online trading platforms such as The Electronic National Agricultural Market (eNAM) since April 2016. Thus, the policies, intended to promote more flexibility in cross-market movement of agricultural commodities to enhance market integration, seem to have not yet been greatly effective in reducing price markups across markets. It is argued that policies, seeking to enhance market integration, should focus on facilitating cross-market trade through infrastructure facilities and reducing restrictions on the movement of agricultural commodities and information sharing (Andrle and Blagrave, 2020).

The trends in the volume of market arrivals of tomatoes in the cities, reported in the figures, reveal wide variations across time and space. Wide fluctuations with recurrent drastic surges or drops in the availability (market arrivals) of tomatoes in the cities could be due to weather fluctuations leading to variations in tomato production, infestations of pests or diseases, and inadequate infrastructure (transport and storage) facilities, causing irregular arrivals in the markets. As the larger availability of a commodity reduces the prices, the prices and availability of tomatoes are found to have varied inversely. The figures show that the movements in the prices and market arrivals of the crop have been in opposite directions, which is substantiated by the findings of negative correlation coefficients between them in most of the cities (Table 1). We shall see in our subsequent analysis that the market arrivals have significantly caused the wholesale and retail prices and *vice versa* in most of the cities.

TABLE 1. CORRELATION BETWEEN TOMATO PRICES AND MARKET ARRIVALS

Market (City)	Correlation coefficient between		
	(P_t^w & P_t^r)	(P_t^w & A_t)	(P_t^r & A_t)
Ahmedabad	0.929[a]	0.114	0.116
Bengaluru	0.956[a]	-0.279[a]	-0.336[a]
Bhopal	0.899[a]	-0.701[a]	-0.617[a]
Bhubaneshwar	0.746[a]	-0.089	-0.235[a]
Chandigarh	0.909[a]	-0.276[a]	-0.350[a]
Chennai	0.865[a]	-0.386[a]	-0.455[a]
Dehradun	0.827[a]	-0.072	0.056
Delhi	0.872[a]	-0.256[a]	-0.284[a]
Hyderabad	0.694[a]	-0.028	0.032
Jammu	0.918[a]	-0.138	-0.271[a]
Kolkata	0.977[a]	-0.071	-0.018
Lucknow	0.896[a]	0.266[a]	0.185[b]
Mumbai	0.919[a]	-0.183[b]	-0.261[a]
Patna	0.822[a]	0.058	0.095
Raipur	0.989[a]	-0.058	-0.032
Ranchi	0.944[a]	-0.406[a]	-0.408[a]
Shimla	0.739[a]	-0.365[a]	-0.069
Trivandrum	0.928[a]	-0.297[a]	-0.343[a]

Notes: Superscripts a and b denote significance at the 1 per cent and 5 per cent levels, respectively. P_t^w: wholesale price; P_t^r: retail price; A_t: market arrivals
Source: Author's estimate.

2.3 Descriptive Statistics

The descriptive statistics, such as mean, coefficient of variations, skewness, and excess kurtosis of the prices and market arrivals of tomatoes for each city are reported in Table 2. There are wide spatiotemporal variations in the prices and market arrivals of the crop. The average wholesale prices varied between the lowest of Rs. 1431.9 per quintal in Ranchi and the highest of Rs. 2488.2 per quintal in Trivandrum, and the average retail prices between Rs. 2156.6 per quintal in Bhopal and Rs. 3812.7 per quintal in Kolkata. Naturally, the average retail prices were higher than the average wholesale prices due to marketing margins enjoyed by the retailers, and transport and other transaction costs involved in moving the vegetable from wholesale to retail markets. The average volume of market arrivals was the highest (10612.8 metric tonnes) in Delhi, followed by Hyderabad (9395.6 metric tonnes), Mumbai (6697.4 metric tonnes), and the lowest (453.2 metric tonnes) in Trivandrum. Inter-city variations in the volume of market arrivals could be due to differences in the size of the population and the demand for vegetables across the cities. The variability in the prices and availability of tomatoes show considerable variations across the cities; the coefficient of variations (CV) varies from 45.98 per cent (Chandigarh) to 76.68 percent (Ahmedabad) for the wholesale prices, 41.36 percent (Shimla) to 74.5 percent (Bhopal) for the retail prices, and 28.01 percent (Mumbai) to 129.74 percent (Bengaluru) for the market arrivals. With a few exceptions, the prices were more volatile in the cities located in the major producing regions compared to those in the minor/non-producing regions.

TABLE 2. DESCRIPTIVE STATISTICS, TOMATO PRICES AND MARKET ARRIVALS

Market (City)	Wholesale Price				Retail Price				Market Arrivals			
	Mean	CV (%)	Skewness	Kurtosis	Mean	CV (%)	Skewness	Kurtosis	Mean	CV (%)	Skewness	Kurtosis
Ahmedabad	1548.7	76.68	2.18	6.74	3142.9	52.61	1.58	3.35	5284.6	42.02	0.61	0.08
Bengaluru	1614.2	74.33	2.15	5.81	2605.6	72.75	2.43	8.02	3234.8	129.74	2.95	11.95
Bhopal	1462.9	83.23	3.32	18.69	2156.6	74.50	2.53	10.58	2803.2	33.33	0.35	0.51
Bhubaneshwar	1861.4	68.41	2.93	13.31	2679.2	58.95	2.30	8.25	1089.1	44.65	0.07	0.15
Chandigarh	1826.9	45.98	2.86	14.01	3276.3	45.60	3.19	18.16	1050.8	81.99	7.44	70.19
Chennai	1801.5	63.29	1.89	3.81	3019.8	59.79	2.56	10.91	2986.5	50.79	1.53	3.89
Dehradun	1574.4	52.00	2.33	8.48	3184.3	55.02	2.48	9.67	1297.3	59.92	1.60	6.32
Delhi	1862.7	74.61	2.82	11.12	3432.8	49.04	2.20	9.55	10612.8	32.89	-0.63	1.31
Hyderabad	1512.7	68.30	1.83	4.23	3459.6	74.87	2.02	3.86	9395.6	66.47	3.66	27.25
Jammu	2099.0	50.63	1.68	3.93	3204.5	48.20	3.35	18.47	2004.4	62.42	6.66	68.13
Kolkata	2333.0	56.34	2.17	8.62	3812.7	52.75	1.80	6.50	2271.0	52.64	3.39	23.17
Lucknow	1924.0	72.12	2.27	8.51	2837.6	60.77	2.58	11.59	877.5	43.55	-0.11	-0.48
Mumbai	1757.6	59.76	2.10	6.29	3180.7	53.51	2.00	6.57	6697.4	28.01	0.59	1.22
Patna	1989.6	72.57	1.85	5.10	3577.5	58.99	1.45	3.48	1055.4	67.16	1.10	1.03
Raipur	1569.9	67.12	2.02	6.43	2547.2	60.67	2.46	10.11	543.1	64.90	0.64	-0.77
Ranchi	1431.9	70.83	2.17	7.14	2682.9	59.03	2.05	7.90	935.0	82.23	4.26	24.37
Shimla	1984.7	46.85	1.49	2.88	3351.8	41.36	2.33	10.10	550.1	62.91	1.44	5.38
Trivandrum	2488.2	50.59	2.09	5.59	3431.2	46.13	2.45	9.34	453.2	95.02	4.86	29.49

Notes: The average prices are in Rupees per quintal, and average market arrivals are in metric tonnes. CV: coefficient of variations.
Source: Author's estimate.

Both wholesale and retail prices show positive skewness for all the cities, signifying that positive spikes are more pronounced and prevalent than negative ones. Both the prices are highly skewed, with positive skewness values greater than 2 in most of the cities. The prices also display significant positive kurtosis for all the cities, indicating the presence of a high degree of extreme values. The market arrivals show significant positive skewness for all the cities except Delhi and Lucknow, and positive kurtosis for all the cities except Lucknow and Raipur. The positive and considerably high values of skewness and kurtosis are indicative of substantial asymmetry and nonnormality in the distribution of prices and market arrivals, and more of the variations is the result of their extreme deviations. Climate change and unpredictable fluctuations in weather leading to droughts, floods, and pest attacks, causing variations in market arrivals could be responsible for the wide fluctuations in prices. Government regulations, market structure, traders' market power, and inadequate infrastructure facilities could be the other reasons for price fluctuations.

2.4 Stationarity of the Variables

We have checked the time-series properties (stationarity or non-stationarity) of the log-transformed price and market arrival data, applying various tests for a unit root viz., the Augmented Dickey-Fuller (ADF) test due to Dickey and Fuller (1979, 1981), the Phillips-Perron (PP) test due to Phillips and Perron (1988) and the DF-GLS test proposed by Elliott et al. (1996). We have employed various unit-root tests to ensure the robustness of the results. The lag length included in the tests was selected by the Akaike Information Criterion (AIC). The estimated test statistics for the wholesale and retail prices and market arrivals of tomatoes are reported in Table 3. The null hypothesis of a unit root is unambiguously rejected by all the tests for all the variables in their levels for all the cities, indicating that all the variables are characterized as stationary processes and hence integrated of order zero, I(0). These results suggest that the prices and availability of tomatoes followed a stationary rather than non-stationary process, and any shocks to them were transitory, leaving no persisting effect on them. This finding contradicts much of the existing literature, which finds these variables to be non-stationary. The differences in the findings regarding stationarity/non-stationarity of the variables between our study and the past studies may be attributed to the differences in the data set, frequency of the data, the study period and market centres chosen, unit root tests applied, etc.

TABLE 3. UNIT ROOT TEST RESULTS FOR STATIONARITY IN TOMATO PRICES AND MARKET ARRIVALS

Market (City)	Wholesale Price			Retail Price			Market Arrivals		
	ADF	PP	DF-GLS	ADF	PP	DF-GLS	ADF	PP	DF-GLS
Ahmedabad	-7.136	-	-8.053	-6.033	-	-5.995	-7.134	-	-7.152
	(2)[a]	6.080[a]	(4)[a]	(2)[a]	5.640[a]	(2)[a]	(2)[a]	6.479[a]	(2)[a]
Bengaluru	-7.266	-	-5.767	-5.503	-	-5.284	-2.438	-	-2.877
	(2)[a]	6.831[a]	(3)[a]	(3)[a]	6.576[a]	(3)[a]	(2)	3.342[c]	(1)[c]
Bhopal	-6.864	-	-8.015	-7.187	-	-7.237	-6.339	-	-5.088
	(3)[a]	5.975[a]	(4)[a]	(1)[a]	6.186[a]	(1)[a]	(2)[a]	7.089[a]	(1)[a]
Bhubaneshwar	-6.662	-	-6.075	-7.591	-	-7.079	-6.106	-	-5.493
	(2)[a]	5.952[a]	(1)[a]	(1)[a]	6.142[a]	(1)[a]	(2)[a]	5.971[a]	(1)[a]
Chandigarh	-6.051	-	-5.738	-5.846	-	-5.855	-4.322	-	-4.334
	(2)[a]	6.601[a]	(2)[a]	(2)[a]	6.611[a]	(2)[a]	(3)[a]	7.463[a]	(3)[a]
Chennai	-6.204	-	-5.390	-5.320	-	-5.196	-3.479	-	-3.305
	(2)[a]	6.005[a]	(3)[a]	(3)[a]	6.650[a]	(3)[a]	(3)[b]	5.985[a]	(3)[b]
Dehradun	-5.924	-	-5.478	-6.448	-	-6.187	-3.546	-	-2.955
	(2)[a]	6.243[a]	(2)[a]	(2)[a]	6.540[a]	(2)[a]	(1)[b]	4.435[a]	(1)[b]
Delhi	-5.768	-	-5.767	-5.999	-	-5.743	-5.815	-	-5.760
	(2)[a]	6.638[a]	(2)[a]	(2)[a]	6.578[a]	(2)[a]	(2)[a]	8.452[a]	(2)[a]
Hyderabad	-6.350	-	-6.317	-6.015	-	-6.002	-4.756	-	-3.860
	(2)[a]	6.174[a]	(2)[a]	(2)[a]	5.939[a]	(2)[a]	(1)[a]	6.535[a]	(1)[a]
Jammu	-5.548	-	-5.521	-6.163	-	-5.986	-4.718	-	-4.666
	(2)[a]	6.382[a]	(2)[a]	(2)[a]	6.839[a]	(2)[a]	(1)[a]	5.570[a]	(1)[a]
Kolkata	-7.377	-	-5.274	-7.462	-	-5.083	-7.189	-	-4.315
	(2)[a]	5.950[a]	(2)[a]	(2)[a]	5.762[a]	(2)[a]	(3)[a]	10.45[a]	(3)[a]
Lucknow	-7.226	-	-7.143	-7.213	-	-7.124	-5.674	-	-2.569
	(1)[a]	5.996[a]	(1)[a]	(1)[a]	5.904[a]	(1)[a]	(1)[a]	9.210[a]	(1)
Mumbai	-6.339	-	-6.076	-6.587	-	-6.502	-5.548	-	-4.167
	(2)[a]	6.439[a]	(2)[a]	(2)[a]	6.869[a]	(2)[a]	(2)[a]	7.160[a]	(3)[a]
Patna	-6.038	-	-6.336	-7.036	-	-7.159	-6.512	-	-6.335
	(2)[a]	5.412[a]	(1)[a]	(2)[a]	5.980[a]	(1)[a]	(1)[a]	6.356[a]	(1)[a]
Raipur	-7.163	-	-6.899	-7.420	-	-6.965	-3.948	-	-3.971
	(2)[a]	6.014[a]	(1)[a]	(1)[a]	5.551[a]	(1)[a]	(3)[b]	7.634[a]	(3)[a]
Ranchi	-6.798	-	-6.587	-7.363	-	-7.170	-5.913	-	-2.634
	(2)[a]	5.789[a]	(1)[a]	(1)[a]	5.827[a]	(1)[a]	(2)[a]	7.077[a]	(1)
Shimla	-6.187	-	-5.370	-5.715	-	-5.718	-4.297	-	-4.068
	(2)[a]	6.396[a]	(3)[a]	(3)[a]	7.090[a]	(3)[a]	(3)[a]	5.559[a]	(3)[a]
Trivandrum	-9.322	-	-5.736	-5.284	-	-5.067	-3.766	-	-3.081
	(1)[a]	6.088[a]	(2)[a]	(3)[a]	6.542[a]	(3)[a]	(2)[b]	7.933[a]	(3)[b]

Notes: Superscript a, b and c denote significance at the 1 per cent, 5 per cent and 10 per cent levels, respectively. Figures in parentheses are number of lags selected by the Akaike Information Criterion (AIC).
Source: Author's estimate.

III

METHODOLOGY

Given that the prices and market arrivals of tomatoes are stationary I(0) processes, a standard vector autoregressive (VAR) model can be used to examine the dynamic relationships that exist between the variables, interacting with each other.

Using the model, the Granger-causality test can be conducted to determine interdependencies and the nature of dynamic relationships between the variables.

For evaluating the vertical integration of the markets, we need to specify the VAR with those variables, which are responsible for dynamic interactions or perceived causal relationships between them. As we have devaluated the vertical integration of tomato markets in terms of the dynamics of price transmission across the wholesale–retail supply chain in conjunction with the availability of the crop in the markets by investigating the interconnectedness among market arrivals and wholesale and retail prices, the VAR is specified with $X_t = [P_t^w, P_t^r, A_t]'$ as a (3×1) vector of endogenous time-series variables comprising wholesale prices (P_t^w), retail prices (P_t^r) and market arrivals (A_t) of tomatoes, and the reduced-form basic VAR(*k*) model with *k* lags of the variables is written as

$$X_t = \alpha + \Pi_1 X_{t-1} + \Pi_2 X_{t-2} + \cdots + \Pi_k X_{t-k} + \varepsilon_t\,,\ t = 1, \ldots, T. \qquad (1)$$

where Π_j $(j = 1, 2, \ldots, k)$ are (3×3) coefficient matrices, α is a (3×1) vector of deterministic regressors, and ε_t is a (3×1) vector of white noise processes with zero mean and time-invariant positive definite covariance matrix, $\sum_\varepsilon$ (for details, see Lütkepohl, 2005, 2007; Nachane, 2006).

The reduced-form VAR can be expressed as a system of three equations.

$$P_t^w = \alpha_1 + \sum_{j=1}^{k} \pi_{11}^{j}\, P_{t-j}^w + \sum_{j=1}^{k} \pi_{12}^{j}\, P_{t-j}^r + \sum_{j=1}^{k} \pi_{13}^{j}\, A_{t-j} + \varepsilon_{1t} \qquad (1.1)$$

$$P_t^r = \alpha_2 + \sum_{j=1}^{k} \pi_{21}^{j}\, P_{t-j}^w + \sum_{j=1}^{k} \pi_{22}^{j}\, P_{t-j}^r + \sum_{j=1}^{k} \pi_{23}^{j}\, A_{t-j} + \varepsilon_{2t} \qquad (1.2)$$

$$A_t = \alpha_3 + \sum_{j=1}^{k} \pi_{31}^{j}\, P_{t-j}^w + \sum_{j=1}^{k} \pi_{32}^{j}\, P_{t-j}^r + \sum_{j=1}^{k} \pi_{33}^{j}\, A_{t-j} + \varepsilon_{3t} \qquad (1.3)$$

where π_{ij}^{j} is the $(i, j)^{\text{th}}$ element of the matrix Π_j in system (1).

The structure of the VAR model provides information about a variable's forecasting ability for other variables which can be evaluated by the Granger causality test, imposing appropriate coefficient restrictions in the equations (Granger, 1969). The linear coefficient restrictions implied by Granger non-causality may be tested using the Wald test statistic. The dynamic interaction among the variables included in the VAR was assessed by conducting pair-wise Granger causality test.

3.1 Price Dynamics in the Supply Chain

To examine whether price signals were transmitted from wholesale to retail markets or *vice versa* in the supply chain and to check if there exists any dynamic causal relationship between the prices and availability of tomatoes, we have conducted pair-wise Granger causality tests by using the parameter estimates of the equations in the VAR model, involving market arrivals and both the prices as endogenous variables for each of the cities. The optimum number of lags, included in the VAR models, were selected by the Akaike Information Criterion (AIC).

Table 4 reports the estimated test statistics along with their associated probability values for testing the null hypothesis of Granger non-causality between the wholesale and retail prices, and between the prices and market arrivals. The prices have exhibited unidirectional price transmission from wholesale to retail levels in 17 (94 percent) cities, and from retail to wholesale levels in 6 (33 percent) cities out of 18. We find the wholesale prices to cause the retail prices in all the cities except Ahmedabad, as the Granger non-causality can be rejected for all the cities except this one. Since the retail prices are set by adding a mark-up over the wholesale prices, it is quite natural that the wholesale prices have significant effects on the retail prices in almost all the cities. This is quite consistent with the price setting behaviour of the retailers of any commodity as suggested by economic theories. Due to seasonality in production and perishability of the crop along with inadequate storage facilities and the inelastic nature of demand, prices at the wholesale level are transmitted to the retail level. However, large transfer costs due to poor infrastructure, transportation, and communication services might have affected the price transmission process. Marketing margins were also found to be large due to high transfer costs. For instance, farmers' share in the final consumer price of tomato in Delhi was estimated at 33.5 percent, with traders' mark-up of 21.3 percent (including transportation cost, *mandi* fees, commission charges, and loading/unloading charges to the extent of 16.0 percent and their margin of 5.3 percent), wholesalers' mark-up of 16.1 per cent and retailers' mark-up of 29.1 per cent (Roy et al., 2024).

It is also evident that the retail prices have significantly caused the wholesale prices in the case of 6 (33 percent) cities (viz., Ahmedabad, Dehradun, Kolkata, Lucknow, Mumbai, and Raipur), as the Granger non-causality running from the retail to wholesale prices can be rejected in their cases. Wholesale markets seem to have incorporated price signals from retail markets. The prices further display bidirectional transmission – from wholesale to retail and *vice versa* in 5 (28 percent) cities (viz., Dehradun, Kolkata, Lucknow, Mumbai, and Raipur), as the results have displayed bidirectional causality (feedback effects) between the wholesale and retail prices in their cases. The remaining cities have exhibited unidirectional causality between the prices; either from wholesale to retail or from retail to wholesale.

Overall, price signals were transmitted from wholesale to retail levels in almost all the cities and from retail to wholesale levels in one-third of cases, with more than one-fourth of cities displaying bidirectional causality between the prices. While the retailers set their prices based on wholesale prices, the wholesalers were influenced by the price signals from retail markets in setting their prices, adjusting the quantity of tomatoes they stored or released onto the market. As tomatoes are storable to an extent, whenever wholesale price increases, it usually spills over to retail prices. When retail prices spike because of any issue in the supply chain, the wholesalers also respond to that shock, managing the inventory and adjusting the stored tomato prices. The spillovers from retail to wholesale prices and bidirectional causality between the prices may be attributed, among other things, to the storability of the vegetable (Padhi et al., 2023). The evidence of price transmissions from wholesale to retail levels and/or *vice versa* suggests that the tomato markets are to an extent vertically integrated.

TABLE 4. PAIR-WISE GRANGER CAUSALITY TEST STATISTICS (WALD TEST χ^2 VALUES)

Market/City	Null hypothesis of Granger non-causality					
	$P^w \nrightarrow P^r$	$P^r \nrightarrow P^w$	$A \nrightarrow P^w$	$P^w \nrightarrow A$	$A \nrightarrow P^r$	$P^r \nrightarrow A$
Ahmedabad (4)	4.308	12.97^{b}	12.998^{b}	11.998^{b}	16.189^{a}	5.825
	[0.366]	[0.011]	[0.011]	[0.017]	[0.003]	[0.213]
Bengaluru (2)	9.858^{a}	4.135	5.156^{c}	0.357	7.219^{b}	1.712
	[0.007]	[0.126]	[0.076]	[0.837]	[0.027]	[0.425]
Bhopal (2)	9.574^{a}	1.929	9.385^{a}	9.621^{a}	5.021^{c}	2.579
	[0.008]	[0.381]	[0.009]	[0.008]	[0.081]	[0.275]
Bhubaneshwar (3)	6.984^{c}	2.980	14.325^{a}	8.322^{b}	27.529^{a}	6.223^{c}
	[0.072]	[0.395]	[0.002]	[0.040]	[0.00]	[0.10]
Chandigarh (2)	13.398^{a}	3.562	8.400^{b}	2.246	1.459	1.051
	[0.001]	[0.168]	[0.015]	[0.325]	[0.482]	[0.591]
Chennai (4)	13.226^{a}	3.945	15.351^{a}	3.533	15.615^{a}	2.485
	[0.010]	[0.413]	[0.004]	[0.473]	[0.004]	[0.647]
Dehradun (4)	13.355^{a}	10.379^{b}	2.355	5.899	0.762	3.97
	[0.010]	[0.035]	[0.671]	[0.207]	[0.943]	[0.41]
Delhi (3)	13.18^{b}	3.295	11.14^{b}	13.38^{a}	15.86^{a}	7.15^{c}
	[0.040]	[0.348]	[0.011]	[0.004]	[0.001]	[0.067]
Hyderabad (2)	10.925^{a}	3.412	0.652	0.184	1.753	0.264
	[0.004]	[0.182]	[0.722]	[0.912]	[0.416]	[0.876]
Jammu (1)	6.972^{a}	2.649	2.332	0.007	10.667^{a}	0.143
	[0.008]	[0.104]	[0.127]	[0.931]	[0.001]	[0.705]
Kolkata (3)	9.602^{b}	21.822^{a}	6.086^{c}	14.561^{a}	10.108^{b}	16.463^{a}
	[0.022]	[0.00]	[0.10]	[0.002]	[0.018]	[0.001]
Lucknow (4)	10.842^{b}	8.447^{c}	9.098^{c}	3.668	3.381	2.678
	[0.028]	[0.076]	[0.059]	[0.453]	[0.496]	[0.613]
Mumbai (2)	31.481^{a}	4.531^{c}	0.994	5.593^{c}	5.166^{c}	5.314^{c}
	[0.00]	[0.10]	[0.608]	0.061]	[0.076]	[0.070]
Patna (2)	6.252^{c}	1.549	2.737	4.609^{c}	1.704	10.016^{a}
	[0.044]	[0.461]	[0.254]	[0.10]	[0.426]	[0.007]
Raipur (1)	3.197^{c}	2.689^{c}	10.069^{a}	3.278^{c}	8.929^{a}	0.089
	[0.074]	[0.10]	[0.002]	[0.070]	[0.003]	[0.765]
Ranchi (2)	7.377^{b}	1.228	2.244	1.621	1.152	0.176
	[0.025]	[0.541]	[0.326]	[0.445]	[0.562]	[0.916]
Shimla (3)	10.732^{b}	1.494	0.929	3.781	3.507	6.106^{c}
	[0.013]	[0.684]	[0.818]	[0.286]	[0.320]	[0.10]
Trivandrum (3)	10.047^{b}	1.379	0.268	6.747^{c}	1.554	3.187
	[0.018]	[0.71]	[0.966]	[0.080]	[0.670]	[0.364]

Notes: Figures in parentheses beside the markets are the optimum number of lags in the VAR involving WP, RP and MA, selected by the Akaike Information Criterion (AIC). Figures in square brackets are the probability values. Superscripts a, b and c denote rejection of the null hypothesis of Granger non-causality at the 1 per cent, 5 per cent and 10 per cent levels, respectively. The null hypothesis of Granger non-causality, for example, $P^w \nrightarrow P^r$ denotes wholesale price (P^w) does not Granger-cause retail price (P^r). A: market arrivals.
Source: Author's estimate.

Market arrivals have caused wholesale and retail prices separately in 10 (55.6 percent) cities and both prices in 8 (44 percent) cities. Wholesale prices have significantly influenced market arrivals in 9 (50 per cent) cities, and retail prices in 6 (33 per cent) cities. The findings of bidirectional causality of market arrivals with tomato prices indicate that while market arrivals have significant effects on the prices, the prices have feedback effects on market arrivals, influencing the traders to decide how much to bring tomatoes into the markets. This is likely to happen when the market structure is such that the traders have the power to control the availability of the crop in the markets, regulating the release of stored quantity. In an oligopolistic market structure when a few traders control the supply of the commodity, managing the inventory, this may take place. It is argued that dominant traders in the supply chain can influence the pricing of commodities in an imperfectly competitive market structure, and poor infrastructure, transportation, and communication services hinder the transmission of price signals (see, for example, Abdulai, 2000; Ghoshray, 2011).

Thus, while the variations in the availability of tomatoes have contributed significantly to the volatility in their prices, traders' market power has possibly influenced the price volatility by regulating the availability of vegetables in the markets. The huge spikes in tomato prices may be attributed to its supply shortage which might have been intensified by the traders' market power, enabling them to control their availability leading ultimately to market failure and price distortions.

IV

IMPLICATIONS AND POLICY CONCLUSIONS

This paper attempted to find the proximate reasons for the variability in tomato prices in India, investigating the dynamics of price transmission across wholesale–retail supply chains by looking into the interconnectedness between market arrivals and wholesale and retail prices of the crop. The results amply demonstrate the volatile nature of the prices, as they fluctuated within and between years, with huge spikes at several time points in all the cities. The prices and market arrivals are stationary I(0) processes, and there is substantial asymmetry and nonnormality in their distribution. The results have indicated that the variations in the availability of tomatoes contributed significantly to the variations in wholesale and retail prices. Again, price signals were transmitted from wholesale to retail markets in almost all the cities, and from retail to wholesale markets in one-third of the cities, implying that while the retailers set their prices based on wholesale prices, the wholesalers were influenced by the price signals from retail markets in setting their prices. Based on these results, the variability in tomato prices at the wholesale and retail levels may be attributed to the variations in the availability of the crop. Naturally, irregularity in the availability of tomatoes either due to production failure or due to supply bottleneck for any issue in the supply chain would invariably result in wide variations in their prices.

The evidence of bidirectional causality of market arrivals with tomato prices indicates that while market arrivals have significant effects on the prices, the prices have feedback effects on market arrivals, influencing the traders to decide how much to bring tomatoes into the markets. The traders seem to have influenced the price volatility by controlling the availability of the vegetable in the market which is likely to happen when the market structure is such that the traders have the power to control the availability of the crop in the markets, regulating its quantity they store or release on to the markets. Thus, while the variations in the availability of tomatoes contributed significantly to the volatility in their prices, traders' market power possibly influenced the price volatility by regulating the availability of vegetables in the markets. The huge spikes in tomato prices may be attributed to its supply shortage which might have been intensified by the traders' market power, enabling them to control their availability in the markets leading ultimately to market failure and price distortions.

The results provide useful policy insights. The finding that market arrivals have significantly caused variability in tomato prices suggests the need for improving productivity and transport and storage facilities to increase production and ensure unhindered movement and regular availability of the commodity in the markets in order to reduce price volatility. The presence of regional concentration in tomato production suggests, the need for good transport facilities to transfer the produce from production to consumption centres. Seasonality in tomato production indicates the need for improving storage facilities to ensure its availability throughout the year. Moreover, as temporary supply chain disruptions and crop damage due to adverse weather conditions often lead to sudden spikes in tomato prices, strengthening weather advisory services can help reduce such spikes. The policies to reduce price variability and enhance market integration and efficiency should focus on facilitating trade, improving infrastructure facilities, lowering restrictions on information sharing and movement of the commodity across markets, and promoting competitiveness. An online trading platform such as eNAM can help reduce price volatility and enhance market integration and efficiency by reducing transaction costs, removing information asymmetry between buyers and sellers, and promoting real-time price discovery based on actual demand and supply.

Our study has some limitations, urging for further research. First, we have produced the results by applying a particular model involving a standard VAR. The results can be strengthened by estimating an alternative model with different specifications, lag structures, and variables, which may provide greater confidence in the robustness of the results. Further research may be done in this direction. Second, we have reported asymmetric price adjustments based on visual inspection of the data presented in the figures. The results can be strengthened through the application of formal econometric testing. Further study may be undertaken, to formally investigate symmetric/asymmetric adjustment in the prices, employing an appropriate econometric model. Third, a separate study may be undertaken to analyses how policy interventions have influenced the dynamics of price transmission over time. This may be carried out by applying formal tests for structural breaks at policy intervention dates and then estimating separate VAR models for pre- and post-intervention periods. A study of this type may be undertaken to see the impact of eNAM on the dynamics of price transmission for several agricultural commodities.

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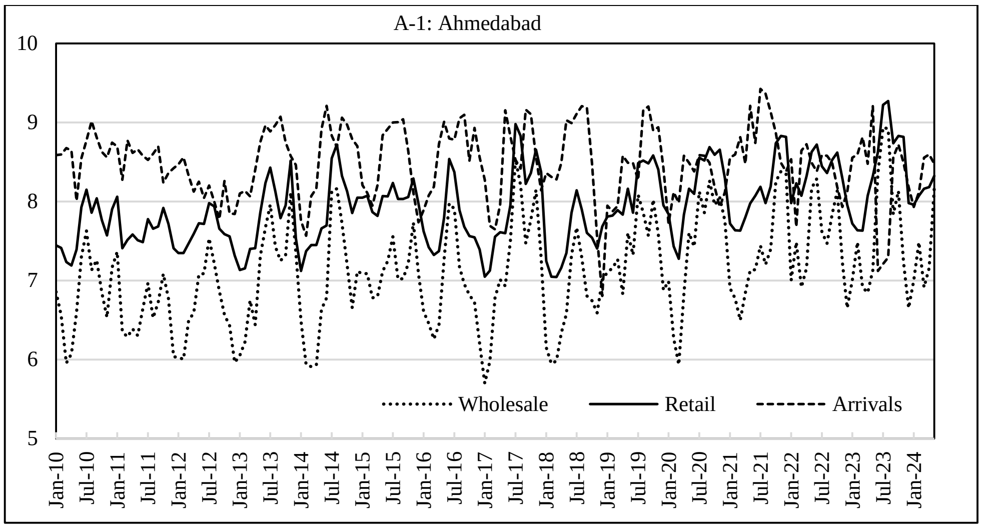
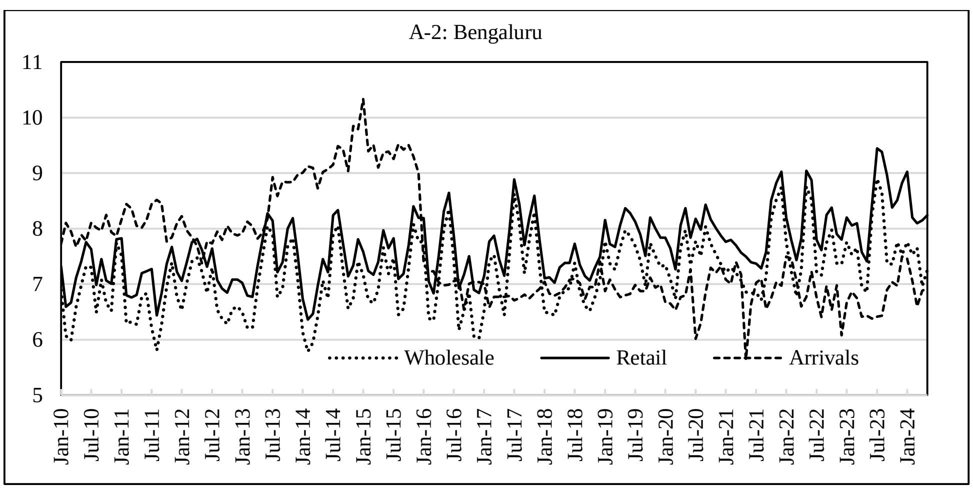
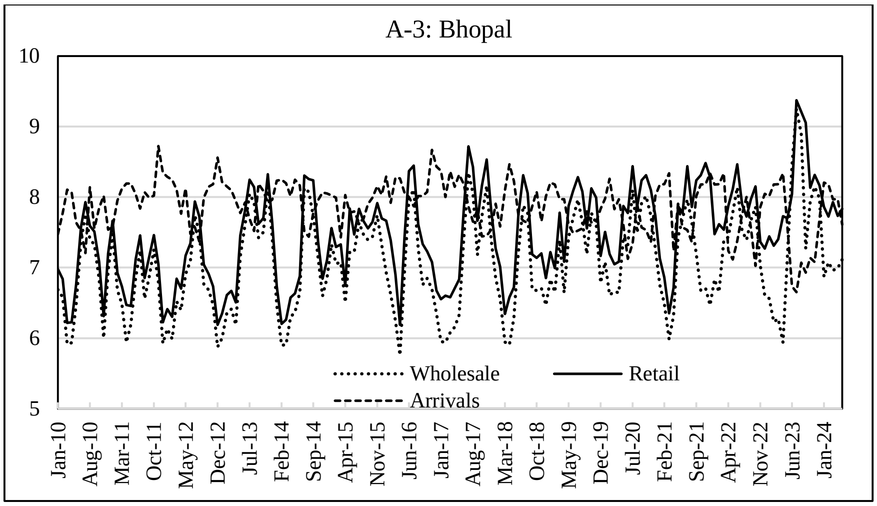
APPENDICES

Figure A: Trends in Tomato Prices and Market Arrivals (both in natural logarithms) in Major Cities






A-3: Bhopal
10
9
8
7
6
5
Wholesale
Retail
Arrivals
Jan-10
Aug-10
Mar-11
Oct-11
May-12
Dec-12
Jul-13
Feb-14
Sep-14
Apr-15
Nov-15
Jun-16
Jan-17
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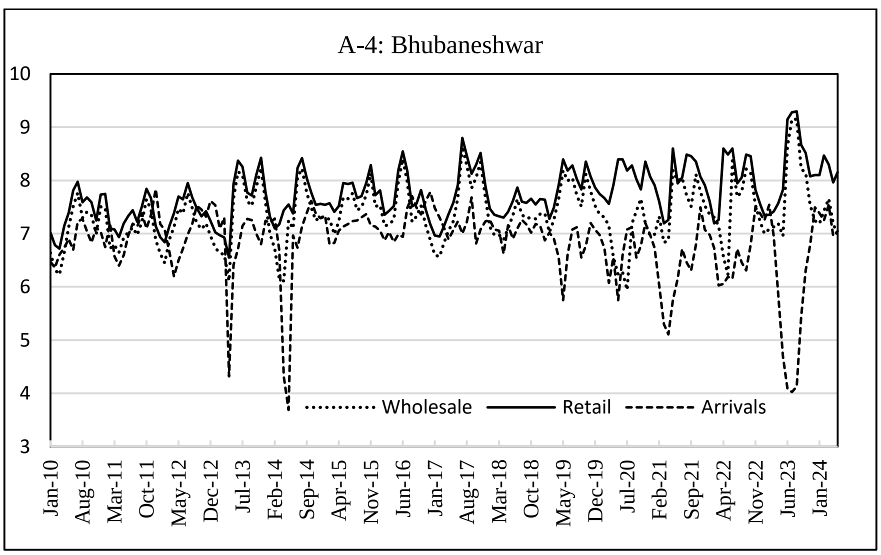
Jan-24


A-4: Bhubaneshwar
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5
4
3
Wholesale
Retail
Arrivals
Jan-10
Aug-10
Mar-11
Oct-11
May-12
Dec-12
Jul-13
Feb-14
Sep-14
Apr-15
Nov-15
Jun-16
Jan-17
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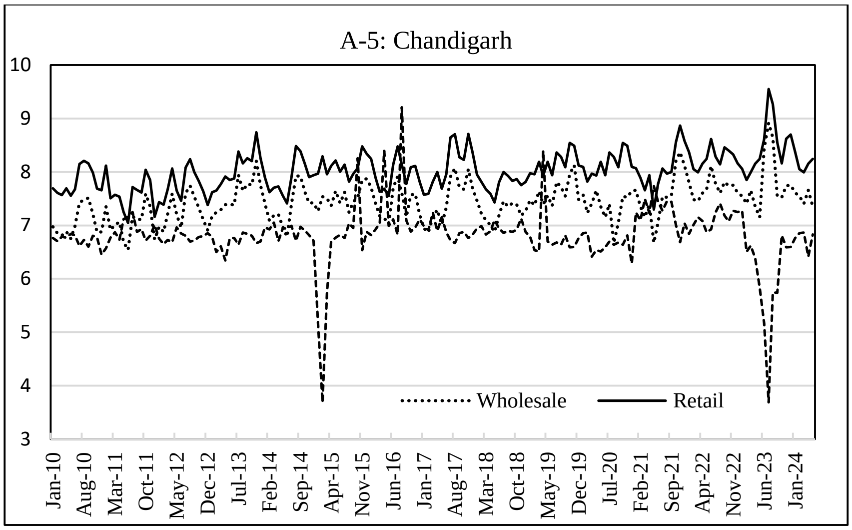
A-5: Chandigarh
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5
4
3
Wholesale
Retail
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May-12
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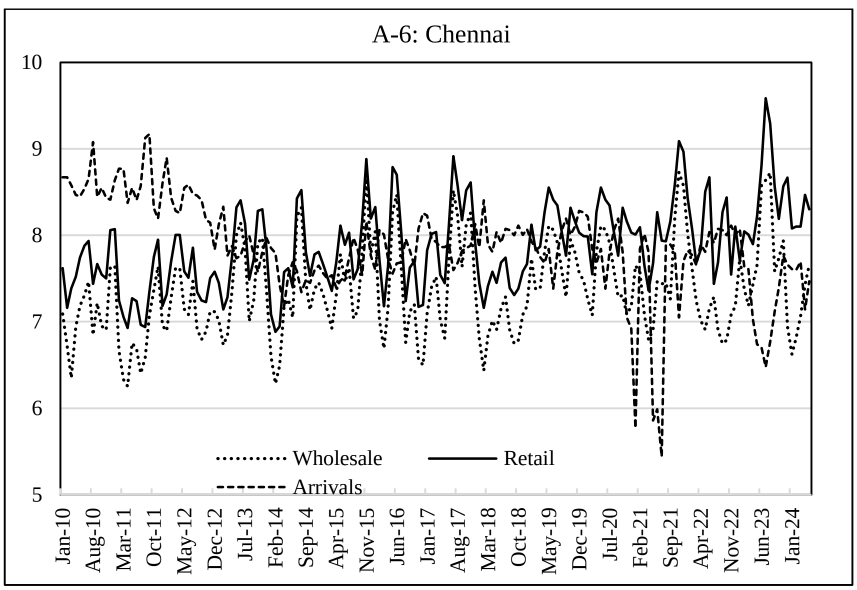
A-6: Chennai
10
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8
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6
5
Wholesale
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Aug-10
Mar-11
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May-12
Dec-12
Jul-13
Feb-14
Sep-14
Apr-15
Nov-15
Jun-16
Jan-17
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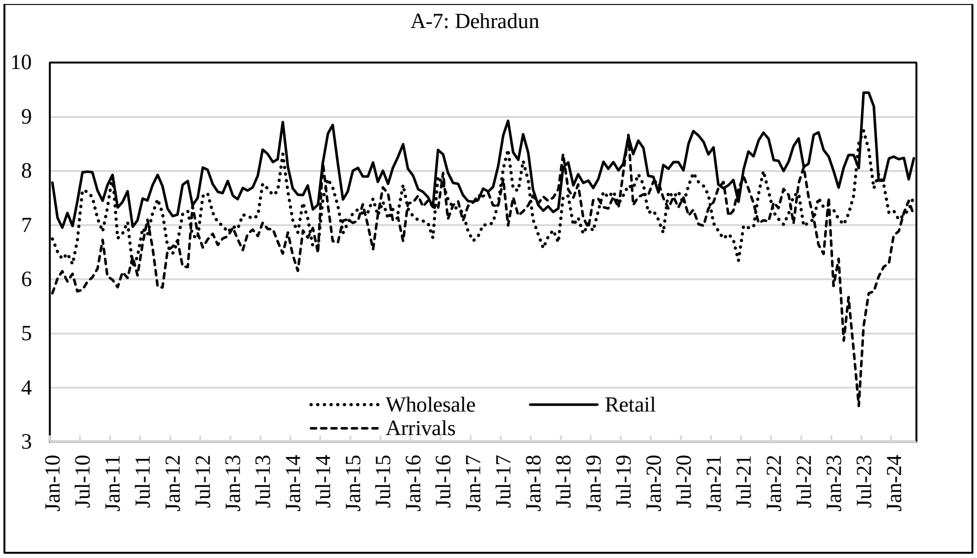
A-7: Dehradun
10
9
8
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5
4
3
Wholesale
Retail
Arrivals
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Jul-11
Jan-12
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Jan-13
Jul-13
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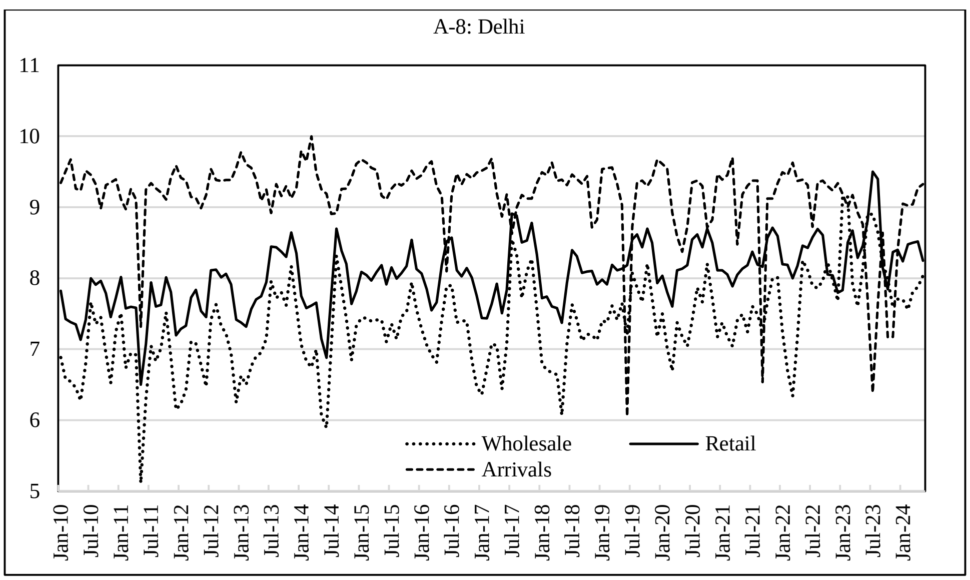
A-8: Delhi
11
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Wholesale
Retail
Arrivals
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Jan-12
Jul-12
Jan-13
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Jan-14
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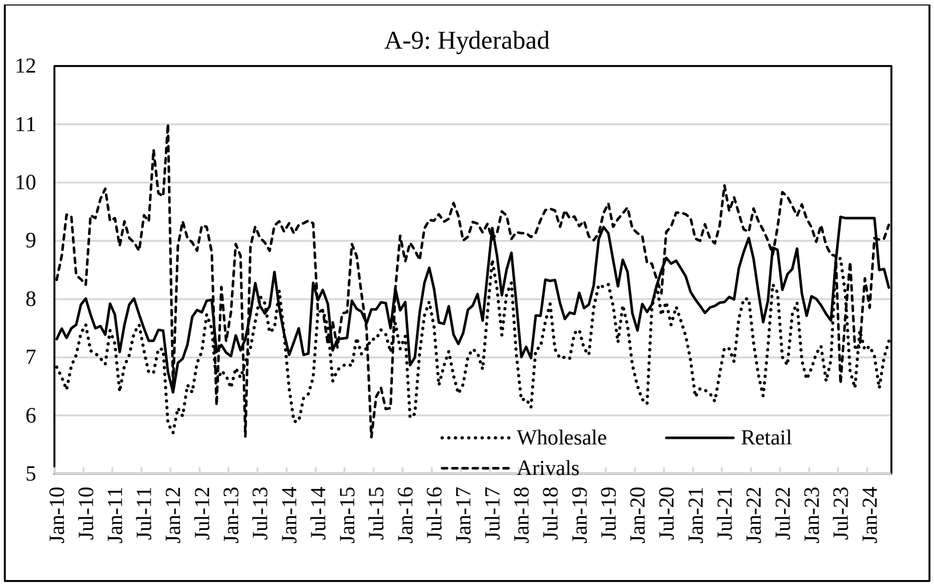
Jan-24


A-9: Hyderabad
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Wholesale
Retail
Arivals
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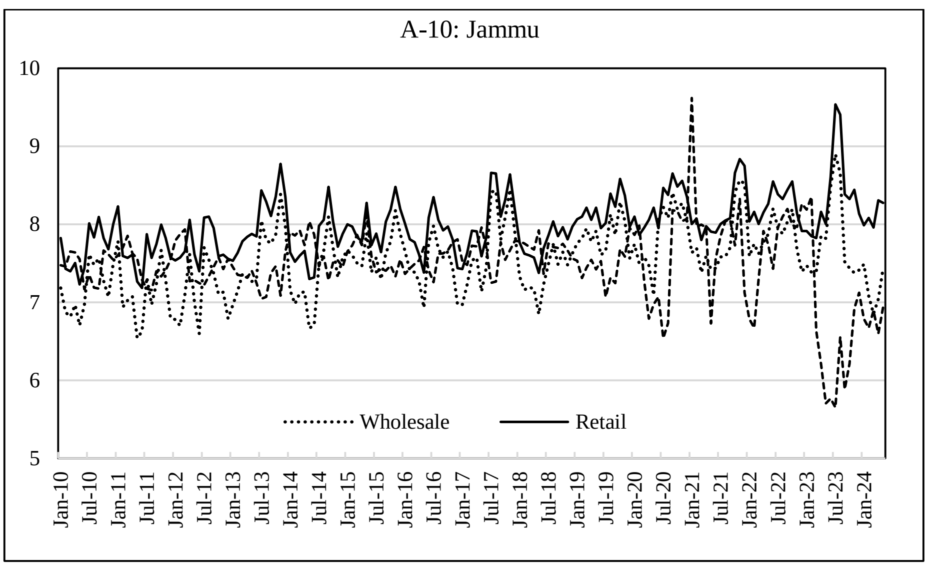
A-10: Jammu
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Wholesale
Retail
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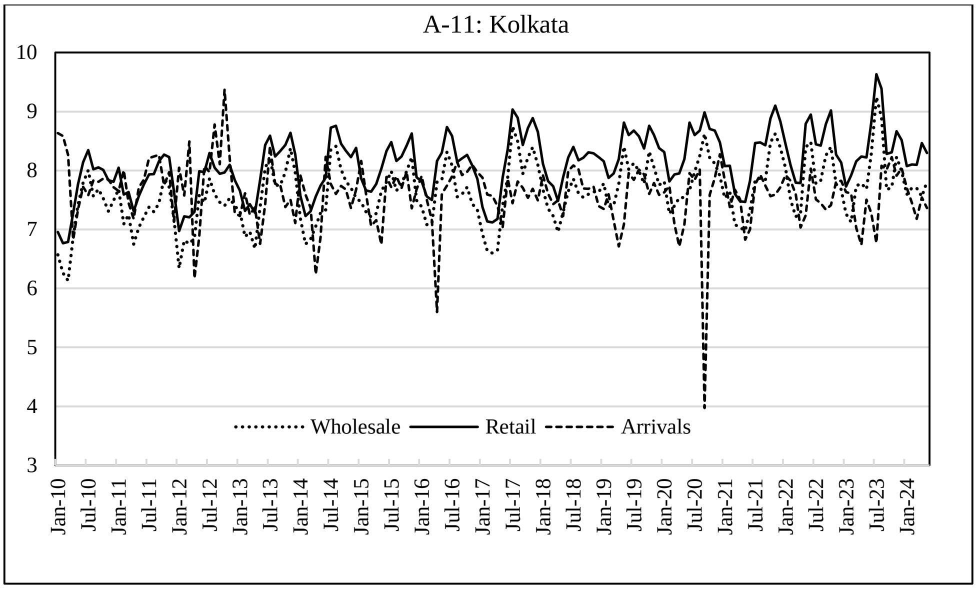
A-11: Kolkata
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Wholesale
Retail
Arrivals
Jan-10
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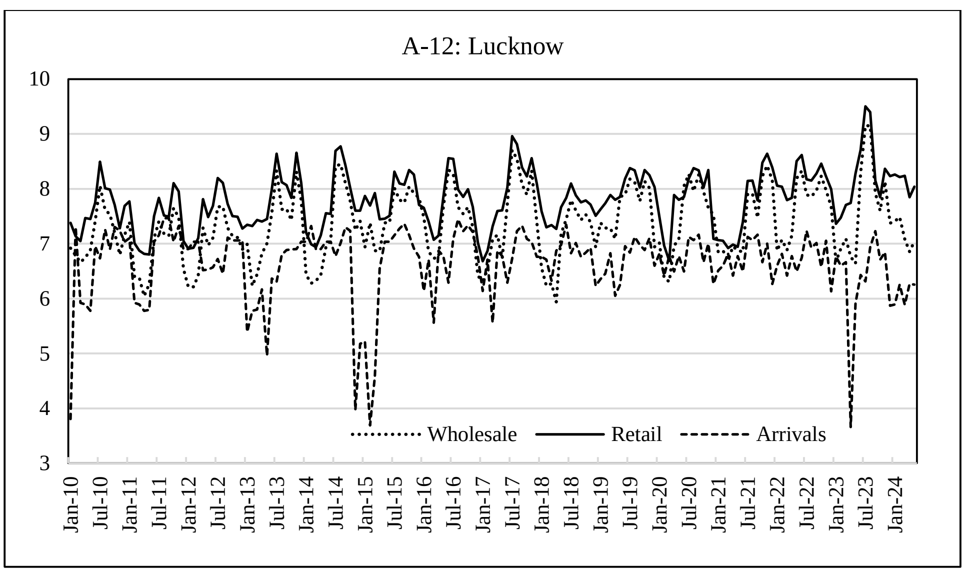
A-12: Lucknow
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Wholesale
Retail
Arrivals
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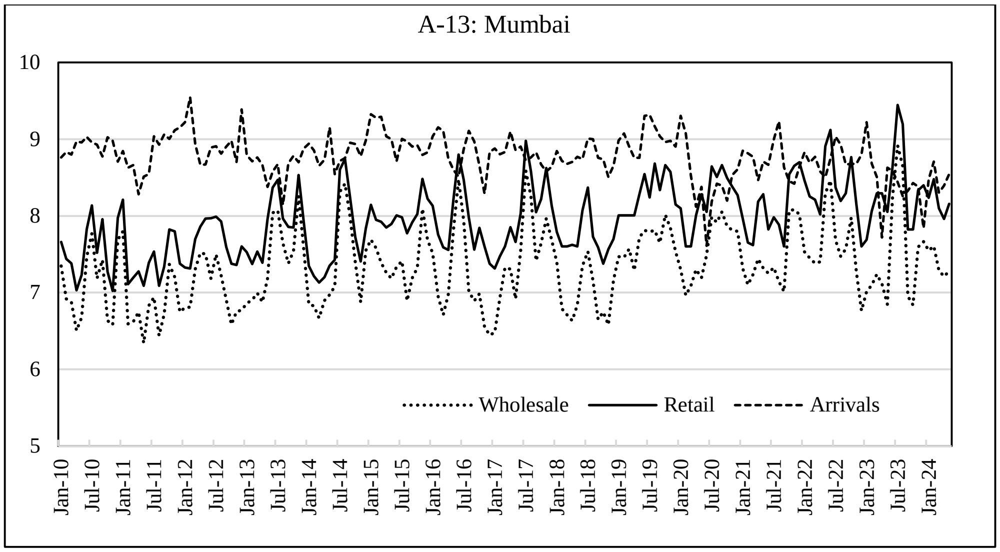
A-13: Mumbai
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Wholesale
Retail
Arrivals
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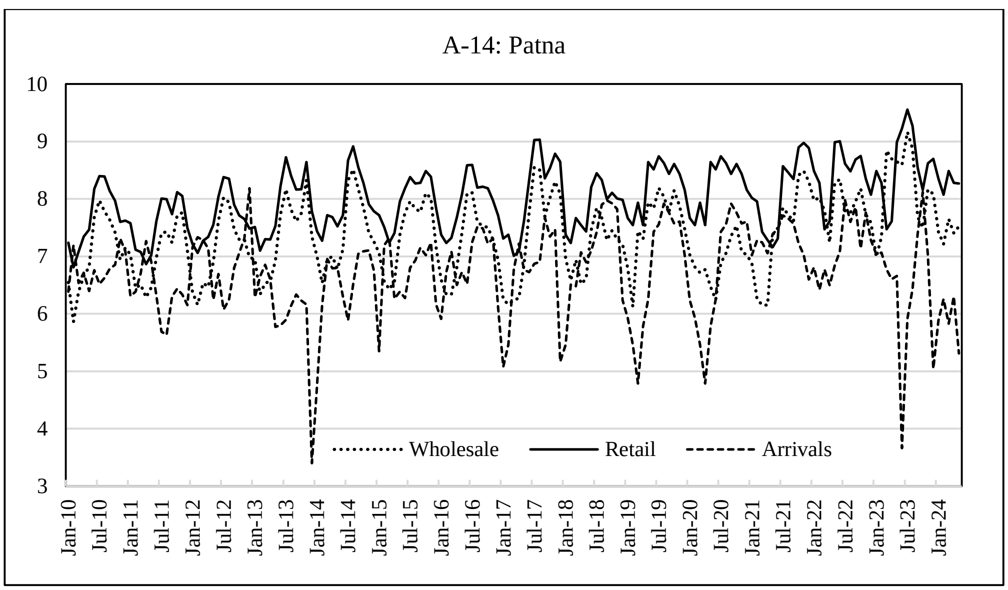
A-14: Patna
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Wholesale
Retail
Arrivals
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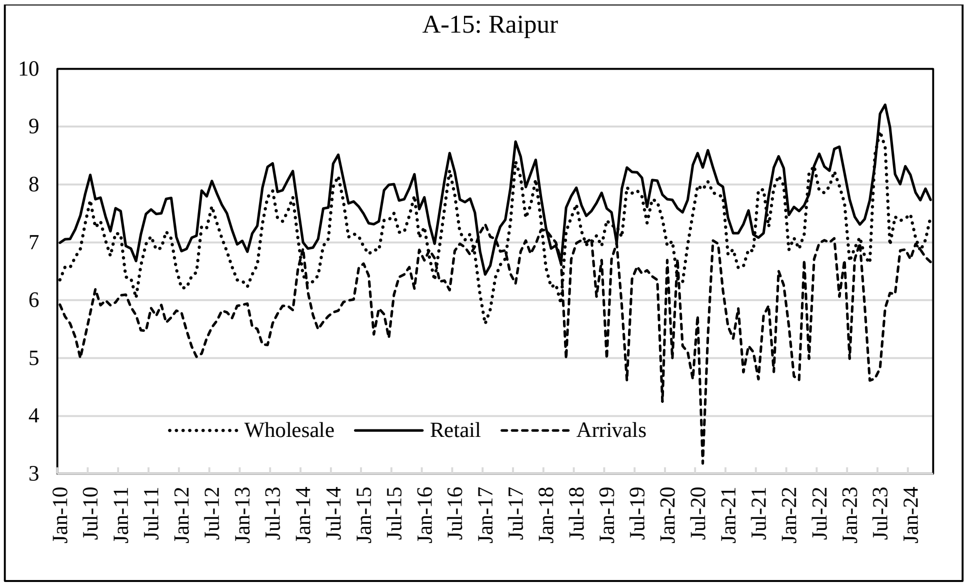
A-15: Raipur
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Wholesale
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Arrivals
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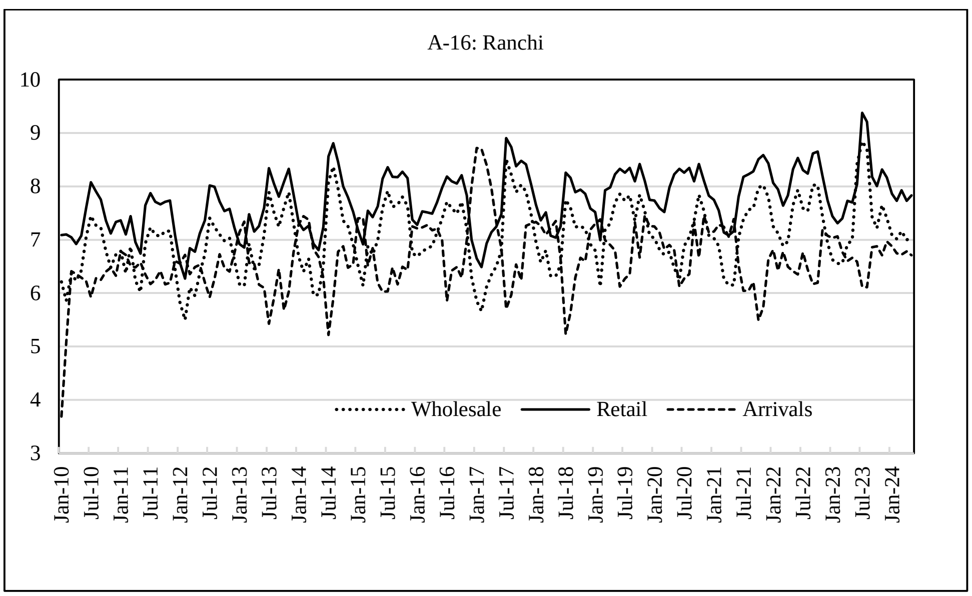
A-16: Ranchi
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Wholesale
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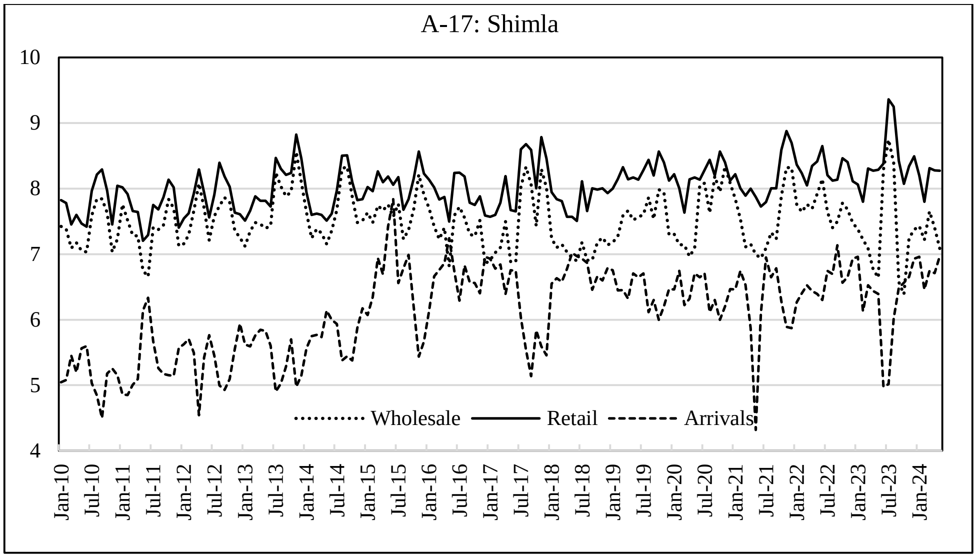
A-17: Shimla
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Wholesale
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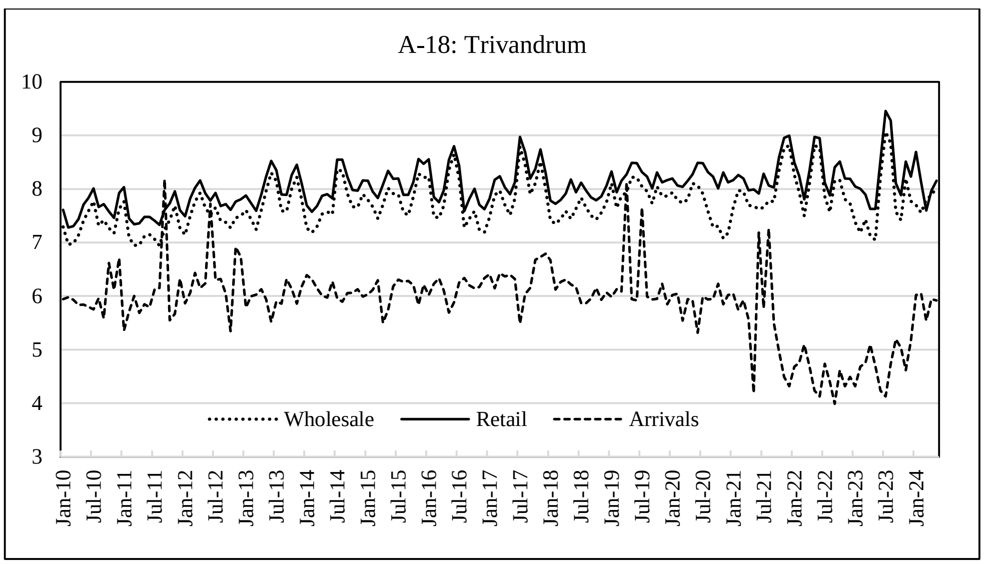
A-18: Trivandrum
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