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The prices of perishable food commodities in India: the impact of the lockdown

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Abstract Onions, potatoes, and tomatoes constitute an important component of the Indian diet. The COVID-19 pandemic in 2020 forced the government to impose a lockdown from 25 March to 31 May. This paper uses granular data to assess the impact of the lockdown on the daily arrivals and wholesale prices of these commodities at three metropolitan markets. The impact was significant and negative on the quantity traded, and positive on prices, but the heterogeneity across commodities and markets was considerable.

Keywords COVID-19; lockdown; food prices; price volatility; India

JEL Codes Q13, Q18

The novel coronavirus disease (COVID-19), first reported in China on 12 December 2019, has turned out to be one of the most severe pandemics in the history of mankind. The pandemic has caused an unprecedented health crisis in both developing and developed countries. The novel coronavirus spreads multiplicatively through human contact. No medical solution has proven to be curative; the global community has been struggling to contain its human-to-human spread via preventive measures – self-sanitization, face masks, and social distancing – and most countries took the extreme step of imposing lockdowns.

The lockdowns severely restricted the mobility of people; transport, travel, and logistics; and the provision of goods and services (except the essentials). The restrictions put exceptional pressure on the production, marketing, and distribution of food systems. The adverse effects on the income and food security of the millions of poor engaged in the informal sector, especially in the developing countries – that are home to over 70% of the global poor – nearly led the social and economic systems to break down (Ceballos, Kannan, and Kramer 2020; Gupta and Kishore 2020; Ivanov 2020; Laborde, Martin, and Vos 2020; Elleby et al. 2020; Ray and Subramaniam 2020).

The first COVID-19 infection in India was traced on 30 January 2020 – to a student returning from China. Recognizing the mode of the disease and its speed of transmission, the Government of India (GoI) announced a complete three-week lockdown on 24 March 2020 and implemented it from the following day. The lockdown coincided with the harvesting of winter crops.

A lockdown disrupts agri-food supply chains in several ways (ADB 2020). Accessing inputs – seeds, fertilizers, pesticides, diesel, and power – becomes difficult for farmers. Labour shortages – on account of stay-at-home and travel restrictions – delay farming operations. Reduced access to output markets raises farm-level post-harvest loss. Trade costs of transportation and logistics increase. The contraction in demand for agricultural commodities lowers producer prices and raises consumer retail prices. The lockdown could have disrupted farming operations, farm incomes, and national food security had the government not quickly exempted farming and domestic trade in agricultural commodities from the strict provisions of the lockdown.

Despite the exemption, however, markets closed frequently, and the inter-state movement of transport vehicles was restricted strictly – inconveniencing farmers, traders, retailers, exporters, and the other participants in the supply chain, raising the cost of transportation and logistics, and significantly reducing the volume of agricultural trade. The market arrival of food commodities from 24 March to 13 April fell 64% from their corresponding levels the previous year (Lowe and Roth 2020) and their wholesale prices rose 10%.

The effect of the lockdown varied by commodity, however: the market supplies of perishable commodities – fruits, vegetables, flowers, and animal products – declined more than that of staple food grains, and their prices dropped significantly due to the worldwide contraction in household and away-from-home demand from eateries, processing industries, and exports. The disruption in global supply chains caused the international prices of dairy and meat products, too, to fall sharply (Elleby et al. 2020).

Later, the government extended the lockdown three times consecutively to 31 May 2020 and issued Standard Operating Procedures to ensure physical distancing for all sectors and contain the spread of the virus. The lockdowns and restrictions affected activity in most economic sectors and social segments, but the loss of employment and income affected poor casual workers the worst (Maitra et al. 2020; Reardon et al. 2020); the impact of a prolonged lockdown on the livelihoods of the poor could be even more severe than of the pandemic itself (Ray and Subramaniam 2020).

Most of the existing evidence reflects the immediate effect of a lockdown; and it is derived from a simple comparison of means, or trends of the parameters of interest, during the lockdown with their corresponding levels in the previous year. The most recent evidence – Yu, Wang, and Feil (2020) for China and Varshney, Roy, and Meenakshi (2020) for India – indicates that COVID-19 did have a little effect on the prices of food commodities, especially of non-perishable staples. Both studies assess the effect of the disease itself and not of the lockdowns or policy measures implemented to contain the spread of the disease. Most countries, including India, have unlocked their economies; as economic activity resumes slowly, however, the case load of COVID-19 increases steeply. Unlike Yu, Wang, and Feil (2020) and Varshney, Roy, and Meenakshi (2020), we examine the effect of lockdowns per se, and not of the case load of COVID-19, as the lockdown restrictions were equally applicable through the country.

Potatoes, onions, and tomatoes – all perishable foods – are widely consumed in India as vegetables, salads, and culinary and processed products. Potatoes and onions can be stored, but little processing took place during the lockdown. This paper assesses the impact of the lockdown, and of the disruption of the supply chain, on the market arrivals and prices of these three important perishable food commodities. Our analysis is based on a long series of price data on periods before and after the lockdown.

Data and descriptive statistics

Our main source of data is the National Horticultural Research and Development Foundation (NHRDF) of the GoI.

Data

The NHRDF provides data on the daily volume of trade and wholesale prices of potatoes, onions, tomatoes, and garlic at the important wholesale markets in India. The daily data on trade volume and wholesale prices was thinly reported for several wholesale markets during the first lockdown; the smaller ones shut for a considerable period or operated intermittently. A complete data series is available for three metropolitan markets: Delhi in the north, Mumbai in the west, and Bengaluru in the south. These markets account for a sizeable share of market arrivals of these commodities. We use the data on these markets for the analysis in this paper.

Changes in commodity output may cause seasonality in prices; to avoid it, we compiled data from January 2018 to August 2020. The total number of observations for each series is 975. The data series on tomatoes was incomplete for the Bengaluru market; we consider only the Delhi and Mumbai markets for tomatoes. Before we analysed the data, we used a suitable imputation technique to estimate the missing values.

Descriptive statistics

India implemented four nationwide lockdowns consecutively, beginning from 25 March 2020 to 31 May 2020. The first lockdown was of 21 days (25 March to 14 April); the second of 19 days (15 April to 3 May); the third of 14 days (4 May to 17 May), and the fourth of 14 days (18 May to 31 May).

Table 1 presents the means and coefficient of variation in the quantities traded of potatoes, onions, and tomatoes in each of the selected markets, and the wholesale prices, during the entire lockdown in 2020 (25 March to 31 May) and for the corresponding periods in 2018 and 2019. For all the commodities, the quantities traded and wholesale prices differ significantly between these periods; the volume of trade was less during the lockdown and the wholesale prices (except of tomatoes) higher.

Compared to the aggregates traded in the three markets in 2019, the corresponding aggregates during the lockdown in 2020 fell 61% for onions, 41% for potatoes, and 36% for tomatoes. Prices increased 19% for onions and 61% for potatoes but declined 39% for tomatoes. The volatility was considerable; the coefficient of variation of the quantities traded increased significantly for all the commodities in all the markets during the lockdown. The pattern of wholesale prices was different, however: the volatility in onion prices was greater than in the prices of potatoes and tomatoes. In fact, there was little, if any, change in the coefficient of variation of the wholesale price of potatoes over time. We considered the trends in the daily arrivals and prices in each market for the periods before and after the lockdown to understand the temporal changes in the quantities traded of potatoes, onions, and tomatoes and their wholesale prices (Figures 1–3).

The maximum and minimum price range (INR per quintal) of onions is (7650, 567) in Delhi, (11000, 450) in Mumbai, and (14000, 523) in Bengaluru. For

Table 1 Quantities traded and wholesale prices of onions, potatoes, and tomatoes

	Quantity (100 kg)				Wholesale price (INR/100kg)			
	Delhi	Mumbai	Bengaluru	Total	Delhi	Mumbai	Bengaluru	Weighted
Onions								
2018	8663	13847	28821	51331	731	975	700	780
	(45.34)	(26.63)	(54.93)	(30.81)	(7.11)	(9.16)	(13.00)	(9.80)
2019	9434	14714	22404	46553	747	925	888	871
	(39.94)	(36.60)	(49.48)	(25.00)	(12.05)	(15.24)	(16.67)	(13.30)
2020	5390	4526	8277	18193	970	1215	985	1031
	(67.64)	(105.81)	(121.48)	(81.90)	(25.05)	(22.80)	(28.73)	(24.37)
Potatoes								
2018	12013	11099	11801	34912	844	1504	1704	1344
	(40.10)	(25.30)	(88.24)	(33.76)	(11.73)	(6.18)	(17.31)	(12.20)
2019	10861	11224	11037	33122	706	1247	1227	1063
	(41.15)	(27.08)	(43.12)	(21.12)	(10.20)	(7.54)	(13.04)	(10.30)
2020	7251	6616	5581	19448	1521	1808	1842	1719
	(68.93)	(67.34)	(49.44)	(48.65)	(11.64)	(6.08)	(10.97)	(7.20)
Tomatoes								
2018	5045	2381		7425	468	561		501
	(31.97)	(17.09)		(21.36)	(35.68)	(22.10)		(20.40)
2019	4516	2458		6974	1286	1452		1345
	(29.72)	(52.36)		(27.98)	(10.03)	(46.63)		(21.70)
2020	3651	808		4459	778	983		807
	(45.14)	(93.32)		(46.80)	(38.17)	(20.04)		(33.50)

Sources Authors' estimates based on data from the NHRDF.
Figures in parentheses are coefficients of variation.

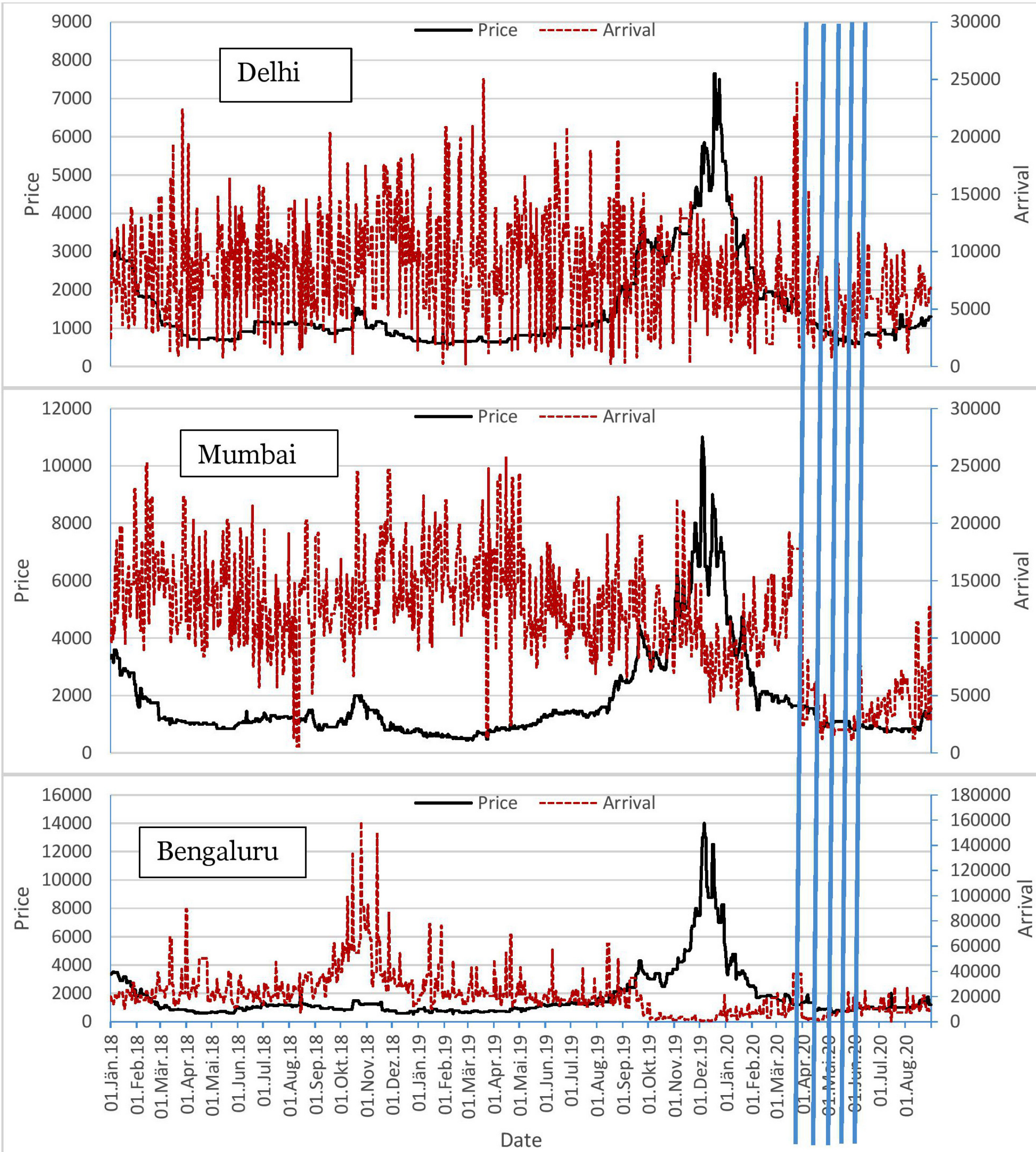

Figure 1 Trend in arrivals and wholesale prices of onions

potatoes the maximum and minimum price range is (1896, 335) in Delhi, (2350, 750) in Mumbai, and (2400, 475) in Bengaluru. For tomatoes it is (3619, 243) in Delhi and (3700, 400) in Mumbai. For tomatoes at the Delhi market the ratio of maximum to minimum price exceeds 10, and it is manifold for the other commodities, too; the price range, or the ratio of maximum to minimum price, in all the three commodities indicates the presence of volatility. The five vertical lines in the figures show the phases of the lockdown in 2020 – each corresponding to 25 March, 14 April, 3 May, 17 May, and 31 May.

The supply chains of all the three commodities were disrupted, especially during the first phase of the lockdown – market arrivals dropped substantially and wholesale prices rose. Although agricultural marketing was exempted from the provisions of the lockdown, the restrictions on inter-state movements of people and transport vehicles raised the cost of transportation and logistics and made it difficult for buyers and sellers of perishable commodities to transfer produce from farm to markets, consumption centres, or processing units.

We calculate the kernel density of the market arrivals of the three commodities at the markets and their

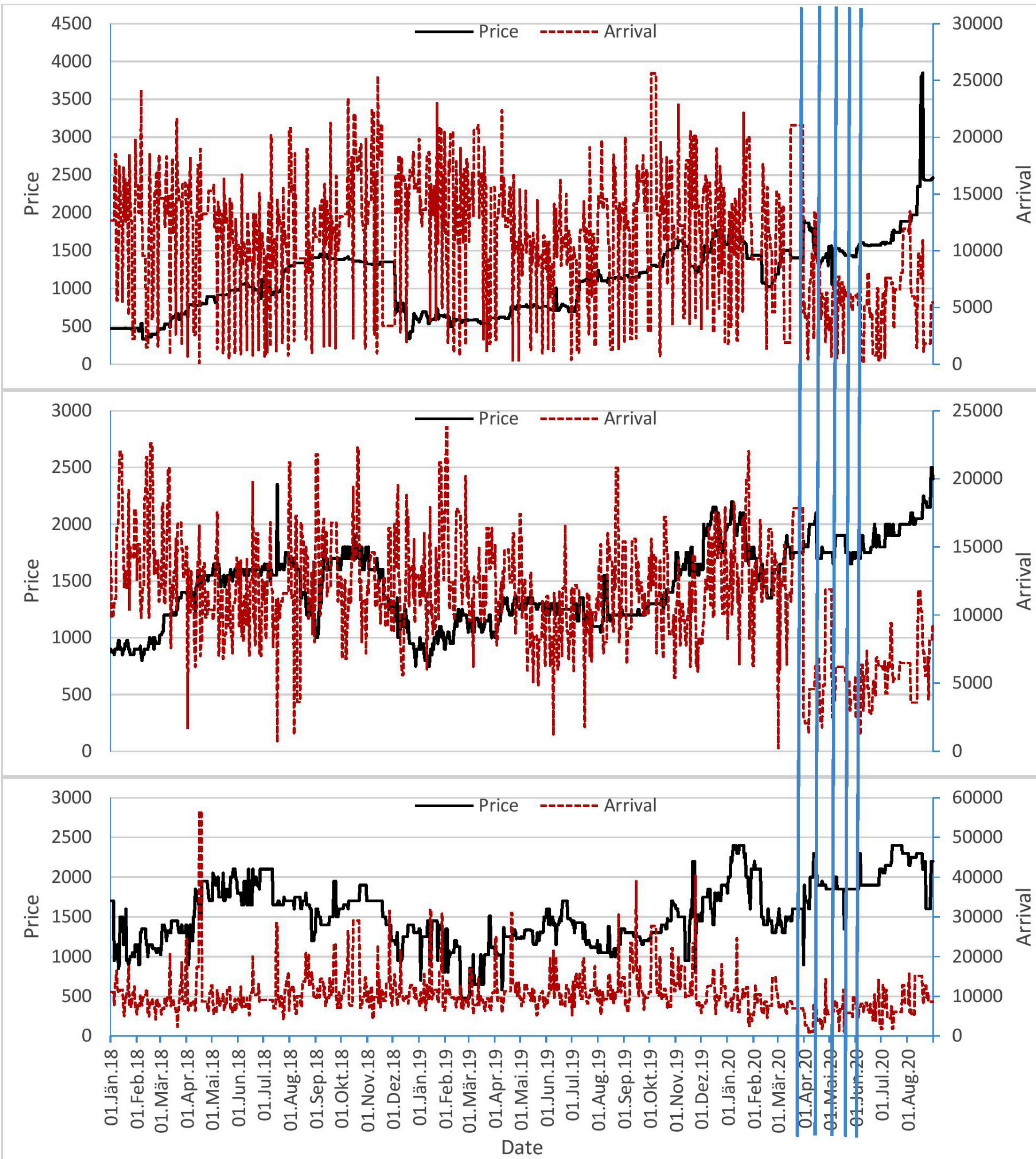

Figure 2 Trend in arrivals and wholesale prices of potatoes

wholesale prices to determine whether the data series follows normality (Figure 4). None of the data series – on market arrivals and wholesale prices of any commodity at any market – is mesokurtic or symmetric, suggesting that the market arrivals and prices did not conform to the normal distribution. To double-check, we applied the Shapiro–Wilk test (Shapiro and Wilk 1965); it confirms the non-normality of the data series (Table A1 in appendix).

Estimation method

The Box–Jenkins autoregressive moving average (ARMA) model is among the most widely used linear time series models in the empirical literature. We apply a time series IGARCH model to understand how differently the lockdown impacted the volume of trade of food commodities and their wholesale prices. The ARMA model, ARMA (p, q), is given by

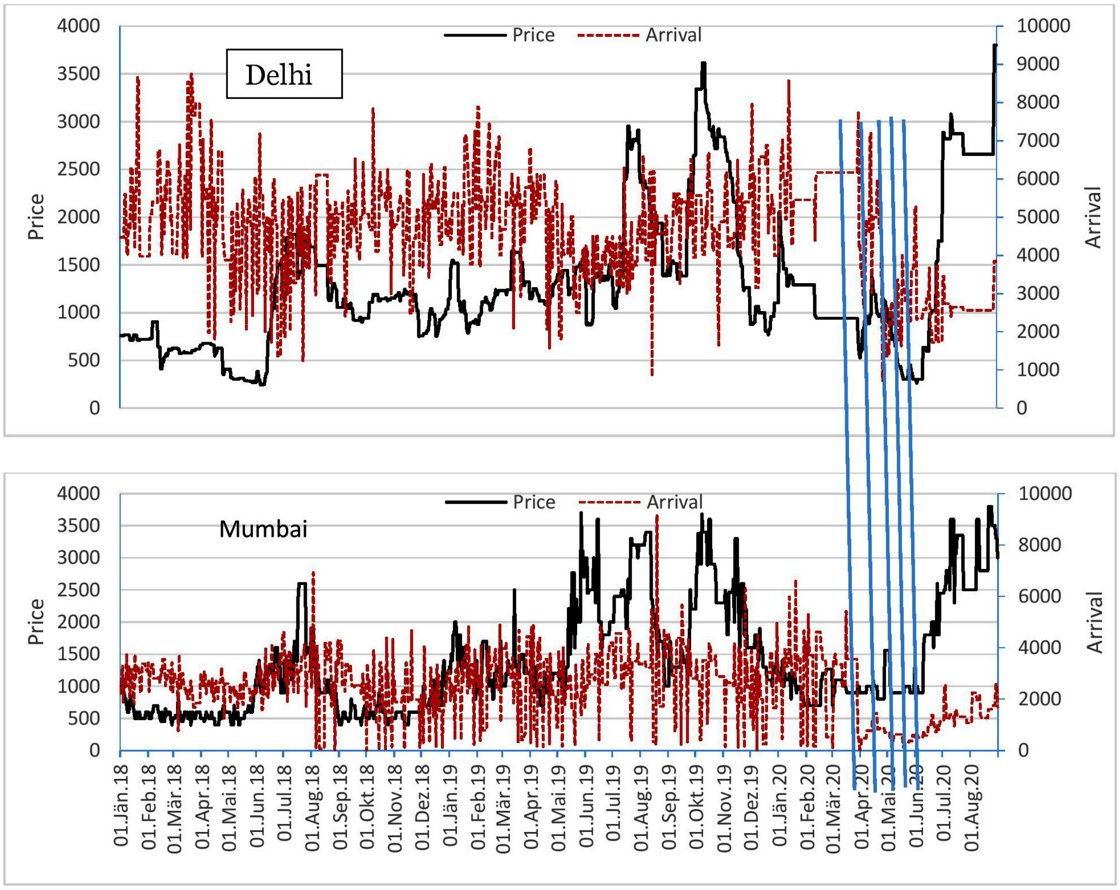

Figure 3 Trend in market arrivals and wholesale prices of tomatoes

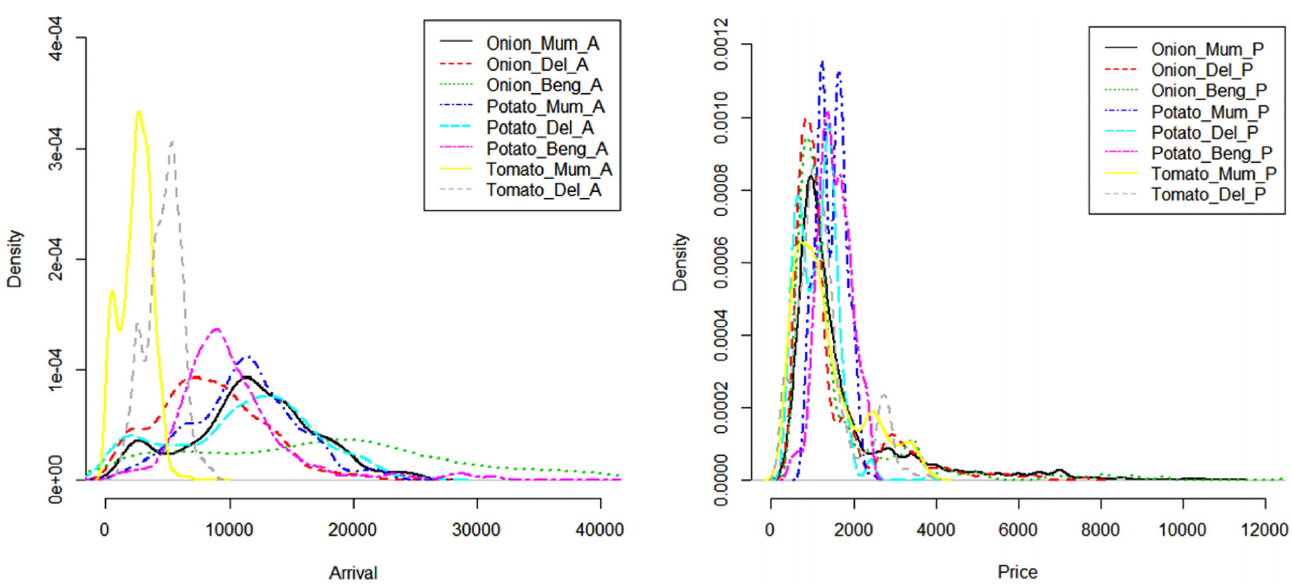

Figure 4 Kernel density of the market arrivals (a) and wholesale prices (b)

$$Y_t = \varnothing_0 + \varnothing_1 y_{t-1} + \varnothing_2 y_{t-2} + ... + \varnothing_p y_{t-p} - \theta_1\varepsilon_{t-1} - \theta_2\varepsilon_{t-2} - ... \theta_q\varepsilon_{t-q} + \varepsilon_t \quad ...(1)$$

or equivalently by,

$$\varnothing(B)\, y_t = \theta(B)\varepsilon_t \quad ...(2)$$

Where $\varnothing(B)$, $\theta(B)$ are the autoregressive and moving average polynomial as defined by:

$$\varnothing(B) = 1 - \varnothing_1 B - \varnothing_2 B^2 - ... \varnothing_p B^p \quad ...(3)$$

and

$$\theta(B) = 1 - \theta_1 B - \theta_2 B^2 - ... - \theta_p B^p \quad ...(4)$$

B is the backshift operator, that is, $By_t = y_{t-1}$

$\boldsymbol{By_t = y_{t-1}}$, p is the order of autoregressive average, and q is the order of moving average. ε_t is a white noise process. This model assumes that the data to be used is stationary, but this assumption rarely holds in practice; most data series are non-stationary and these need to be transformed into a stationary series through proper order of differencing. The resultant model is called an autoregressive integrated moving average (ARIMA) model.

When the series is non-linear and the conditional variance of error term is heteroscedastic, the time series behaviour of the variable of interest cannot be explained adequately by the linear ARIMA model; an autoregressive conditional heteroscedastic Lagrange multiplier (ARCH-LM) test is suggested to check the residuals of ARMA for non-linearity and conditional heteroscedasticity (Engle 1982). Paul et al. (2009) report one of the applications of ARCH-LM test to the real data analysis. The usual ARIMA model cannot represent a series properly if volatility is present; a non-linear time series model is called for.

We ensured the presence of the ARCH effect in the residuals of the fitted ARMA model. To represent the data at hand more precisely, we needed a suitable non-linear time series model. The most popular non-linear time series model is the autoregressive conditional heteroscedastic (ARCH) model (Engle 1982), defined by specifying the conditional distribution of the series ε_t, given the information is available up to time t–1 (Ψ_{t-1}). Then, the process $\{\varepsilon_t\}$ follows ARCH model of order q if the conditional distribution of ε_t, and given the available information Ψ_{t-1}, is defined as

$$\varepsilon_t \mid \Psi_{t-1} \sim N(0, h_t) \quad ...(5)$$

Where h_t is the conditional variance of ε_t is defined as

$$h_t = a_0 + \Sigma_{i=1}^{q} a_i\, \varepsilon_{t-1}^2 \quad ...(6)$$

$A_0 > 0$, $a_i \geq 0$ for all i and $\Sigma_{i=1}^{q} a_i < 1$

However, the ARCH model is not a parsimonious representation. To overcome this disadvantage, Bollerslev (1986) proposed the generalized ARCH (GARCH) model with conditional variance – not only a linear function of past squared shocks but also a linear function of its own lags. The GARCH model has the form

$$h_t = a_0 + \Sigma_{i=1}^{q} a_i\, \varepsilon_{t-1}^2 + \Sigma_{j=1}^{p} b_j h_{t-j} \quad ...(7)$$

A sufficient condition for the conditional variance to be positive is

$a_0 > 0$, $a_i \geq 0$, , i= 1, 2,…,q and $b_j \geq 0$, j= 1, 2, …, p.

The models that explain the changes in conditional variance are known as conditional heteroscedastic models in the time series literature. The widely used volatility models are the ARCH (Engle 1982); GARCH (Bollerslev 1986; Taylor 1986); integrated GARCH (IGARCH) (Engle and Bollerslev 1986); exponential GARCH (EGARCH) (Nelson 1991); and fractionally integrated GARCH (FIGARCH) model (Baillie et al. 1996). Some applications of the GARCH family of models may be found in Paul, Prajneshu, and Ghosh (2009) and Paul, Ghosh, and Prajneshu (2014).

If the AR polynomial of the GARCH representation has a unit root, it is called an IGARCH model, that is, the IGARCH model represents a unit root GARCH process (Engle and Bollerslev 1986). The IGARCH model imposes restriction on the parameters in equation (7) as $\Sigma_{i=1}^{q} a_i + \Sigma_{j=1}^{p} b_j = 1$.

An IGARCH(1,1) model can be written as

$$h_t = a_0 + (1 - b_1)\, \varepsilon_{t-1}^2 + b_1 h_{t-1} \quad ...(8)$$

where $\{\varepsilon_t\}$ is defined as before, and $1 > b_1 > 0$.

The descriptive statistics in the previous section shows that the lockdown impacted both the mean and price volatility. We incorporate a binary indicator in the mean and variance functions to measure the impact in each of the four phases of the lockdown.

Mean equation

$$y_t = \varnothing_0 + \varnothing_1 y_{t-1} + \varnothing_3 ld1_t + \varnothing_4 ld2_t + \varnothing_4 ld3_t + \varnothing_5 ld4_t + \theta_1\varepsilon_{t-1} + \theta_2 S_t + \varepsilon_t$$

Variance equation

$h_t = a_0 + a_1\varepsilon^2_{t-1} + b_1h_{t-1} + c_1ld1_t + c_2ld2_t + c_3ld3_t + c_4ld4_t + a_1 + b_1 = 1$

where, ldi_t (i=1,2,3,4) are the dummies for the four phases of the lockdown.

In the mean equation, $\varnothing_0$ is the constant in mean equation, $\varnothing_1$ is the AR coefficient, and θ_1 is the MA coefficient. $\varnothing_3 - \varnothing_5$ capture the effects of lockdowns 1 to 4 on commodity prices and ε_t as defined in equation 5.

In the variance equation, a_0 is the intercept, a_1 is the ARCH coefficient, b_1 is the GARCH coefficient, and c1–c4 capture the effects of the sequential lockdowns on price volatility.

We include a dummy variable (S_t) for the month in the mean function to account for the seasonality in prices.

We used the maximum likelihood estimation method to estimate the model and the R software package for analysing the data.

Results and discussion

We use the GARCH model to assess the lockdown's impact on commodity prices; to ensure that the model is robust, we begin with testing for autocorrelation and the unit root in the wholesale prices.

Tests for autocorrelation, unit root, and ARCH effect

To test for the autocorrelation, we apply the Box–Pierce test (Box and Pierce 1970). The test statistic rejects the null hypothesis – the wholesale price data is independently distributed – in favour of the alternate hypothesis, that there is serial correlation in the prices of all the commodities and in all the markets (Table 2). Therefore, GARCH model is more appropriate in evaluating the impact of the lockdown on commodity prices.

The other requirement for implementing the GARCH model is that the time series should not have long-term memories, that is, it should be stationary. To know whether a price series has a unit root, we apply the augmented Dicky–Fuller (ADF) test, the Philip–Perron (PP) test, and the Kwiatkowski–Phillips–Schmidt–Shin (KPSS) test.

For the ADF and PP tests the null hypothesis is that the price series has a unit root; for the KPSS test it is that the price series is stationary (Table 3). The price series has a unit root at the level for all the three commodities and in all the markets, but these turn out to be stationary on first differencing.

We conduct the ARCH-LM test on the residual series of the fitted ARIMA model on each of the price series and find that the ARCH effect was significant in the residuals for all the series, leading us to consider the non-linear family of time series model, that is, the GARCH family of models. The ARCH-LM test is conducted as follows:

Let ε_t be the residual series. We use the Lagrange multiplier (LM) test for squared series $\{\varepsilon_t^2\}$ to check for conditional heteroscedasticity. The LM test is equivalent to usual F-statistic for testing H_0: a_i=0, i=1, 2, …, q in the linear regression

$\varepsilon^2_t = a_0 + a_1\varepsilon^2_{t-1} + ... + a_q\, \varepsilon^2_{t-q} + e_t$, t = q+1...T

where e_t denotes the error term, q is the pre-specified positive integer, and T is the sample size.

Let $SSR_0 = \Sigma^T_{t=q+1} (e^2_t - \bar{\omega})^2$, where $\bar{\omega} = \Sigma^T_{t=q+1} \varepsilon^2_t/T$ = /T is sample mean of $\{\varepsilon_t^2\}$, and $SSR_1 = \Sigma^T_{t=q+1} \hat{e}^2_t$, where $\hat{e}_t$ is the least square residual. Then, under H_0, the ARCH-LM test statistic is

$$F = \frac{(SSR_0 - SSR_1)/q}{SSR_1/(T-q-1)}$$

Table 2 Box–Pierce test results in price series

	Onions		Potatoes		Tomatoes	
	stat	prob	stat	Prob	stat	prob
Delhi	958.83	<0.001	931.87	<0.001	938.62	<0.001
Mumbai	952.37	<0.001	917.39	<0.001	894.36	<0.001
Bengaluru	948.53	<0.001	845.55	<0.001		

Table 3 Test results for unit root in price series

	At level						At first difference					
	PP		ADF		KPSS		PP		ADF		KPSS	
	stat	prob	stat	prob	stat	prob	stat	prob	stat	prob	stat	prob
Onions												
Delhi	–7.87	0.67	–2.07	0.55	1.94	0.01	–872.80	0.01	–10.79	0.01	0.12	0.10
Mumbai	–10.30	0.54	–1.64	0.73	2.00	0.01	–620.59	0.01	–11.33	0.01	0.08	0.10
Bengaluru	–13.13	0.38	–2.01	0.57	1.78	0.01	–750.14	0.01	–11.03	0.01	0.06	0.10
Potatoes												
Delhi	–11.89	0.45	–2.23	0.48	5.32	0.01	–1071.06	0.01	–9.88	0.01	0.06	0.10
Mumbai	–21.06	0.06	–2.26	0.47	3.61	0.01	–1020.74	0.01	–11.85	0.01	0.04	0.10
Bengaluru	–21.24	0.06	–2.52	0.36	2.00	0.01	–973.12	0.01	–14.10	0.01	0.05	0.10
Tomatoes												
Delhi	–16.27	0.20	–3.38	0.06	2.21	0.01	–921.44	0.01	–7.96	0.01	0.05	0.10
Mumbai	–14.86	0.27	–2.95	0.18	3.27	0.01	–953.73	0.01	–10.60	0.01	0.03	0.10

The test statistic F asymptotically follows the chi square distribution with q degrees of freedom (Engle 1982).

Impact of the lockdown on prices

In the first step of model building, we fit the suitable ARIMA model to the price series by including exogenous variables, that is, a dummy for each of the four phases of the lockdown. The best model is determined based on the minimum value of different information criteria. We examined the residuals and found, as reported in the previous section, that the ARCH effect is significant. To accommodate the conditional heteroscedasticity, therefore, we chose the appropriate GARCH family of model. The best model is found to be ARMA(1,1)-IGARCH(1,1) model (Table 4).

We decided the best fit of model based on the minimum value of the log likelihood ratio, Akaike information criterion, Bayes information criterion, and the Hannan–Quinn statistic. The distribution of the price series is non-normal; therefore, we assume that the underlying distribution of the error term for the IGARCH model is the Student's t-distribution. The shape parameter of the Student's t-distribution is statistically significant for all the commodities in all the markets, suggesting that our assumption is correct.

The coefficient of AR(1) in the mean function is positive and highly significant for all the commodities in all the markets except for tomatoes in Delhi. That means that the historical prices of the commodities positively impact their prices in the current period, the impact is bigger on onion prices, and the impact in the markets is almost identical. The impact of past prices of potatoes is larger in Delhi than in other markets. The dependency of the current price on its immediate past price is high in all the markets. The coefficient of MA(1) is negative and significant for all the commodities. This suggests that past price shocks have a depressing effect on the current period prices. The effect is pronounced on potato prices.

The wholesale prices of all the commodities increased in all the markets in the first phase of the lockdown, as expected, and the increase is statistically significant. The effect was bigger for onions and tomatoes in Delhi and for potatoes in Mumbai. The prices of all commodities continued to rise in the second phase. Onion prices increased faster in Delhi and Bengaluru but declined marginally in Mumbai. Potato prices, too, increased in all the markets but faster in Mumbai and Delhi. Tomato prices increased faster in Mumbai than in Delhi. The rising trend started tapering off in the third phase of the lockdown, but the effect varied considerably by commodity and by market.

The ARCH and GARCH parameters in the variance function are positive and highly significant in all the commodities and markets, implying that current period volatility in wholesale prices is influenced by the volatility in the immediate past. The GARCH coefficient is larger than the ARCH coefficient,

Table 4 Parameter estimates of ARMA(1,1)-IGARCH(1,1)

	Onions			Potatoes			Tomatoes	
	Delhi	Mumbai	Bengaluru	Delhi	Mumbai	Bengaluru	Delhi	Mumbai
Mean function								
Constant	2849.98*	2547.21*	3295.24*	471.03*	933.97*	1700.00*	760.823*	1021.85*
AR(1)	0.964*	0.976*	0.961*	0.637*	0.532*	0.487*	–0.503*	0.482*
MA(1)	–0.150**	–0.065*	–0.102*	–0.867*	–0.743*	–0.759*	0.554*	–0.728*
Lockdown 1	0.0110***	0.005**	0.007*	0.003**	0.0118**	0.008**	0.003**	0.001**
Lockdown 2	0.048*	–0.003	0.021**	0.005*	0.0210**	0.004*	0.001**	0.032***
Lockdown 3	0.0003	0.0003	0.0001	0.0002	0.0004	0.0002	0.0001	0.0004
Lockdown 4	0.0001	0.0002	0.0001	0.0003	0.0001	0.0002	0.0005	0.0001
Variance function								
Constant	146.62	230.51***	568.19***	752.26*	1895.75*	1407.53*	113.15*	365.34*
ARCH	0.120*	0.154*	0.170*	0.222*	0.032*	0.146*	0.035*	0.310*
GARCH	0.880*	0.846*	0.830*	0.778*	0.833*	0.853*	0.964*	0.680*
Lockdown 1	0.0002**	0.0001***	0.006***	0.0001***	0.008**	0.0001**	0.0009***	0.0009***
Lockdown 2	0.0001**	0.0001**	0.00009***	0.0001***	0.0001***	0.0002***	0.0001***	0.0002***
Lockdown 3	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Lockdown 4	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Shape	2.1*	2.3*	2.1*	2.1*	2.1*	2.2*	2.03*	2.16*
Model selection criteria								
Likelihood ratio	–5425	–5777	–5860	–5046	–5371	–5918	–5696	–6284
Akaike information	11.531	12.291	12.561	10.74	11.430	12.592	12.12	13.368
Bayes information	11.593	12.352	12.623	10.802	11.491	12.654	12.182	13.430
Hannan–Quinn statistic	11.555	12.314	12.584	10.764	11.453	12.616	12.144	13.391

*, ** and *** denote 1%, 5%, and 10% statistical significance, respectively.

suggesting that price volatility is influenced more by the volatility in the immediate past than the immediate squared shocks of the prices. The sum of the ARCH and GARCH coefficients is unity in all the cases. The coefficients of the dummies in the variance function are positive and significant for all the commodities in all the markets during the first and second phases of the lockdown. The lockdown raised the price volatility of all the three commodities, but the heterogeneity in their volatility effects – across commodities and markets and over time – is considerable. The effect of the first phase of the lockdown is larger for onions in Bengaluru, for instance, and for potatoes in Mumbai.

The impact of each phase of the lockdown differed significantly, too. During the second phase the volatility in onion prices declined in Delhi and Bengaluru but remained almost the same in Mumbai; the volatility in potato prices increased in Bengaluru, and decreased in Mumbai, but remained almost the same in Delhi; and the volatility in tomato prices increased. The subsequent phases did not impact the price volatility of any commodity in any market.

Checking the adequacy of the model

In building any model, the residuals validate the assumptions of the error term. To check the adequacy of the fitted ARMA–IGARCH model, we performed several statistical tests on the residuals of the model and on its squared residuals: the weighted Ljung–Box test; the ARCH-LM test, the Nyblom stability test, and the sign bias test (Table A2 in appendix).

The weighted Ljung–Box test checks for autocorrelation in the standardized residuals and standardized squared residuals. It is not significant for any commodity in any market, suggesting that autocorrelation is absent. The ARCH-LM test statistic shows that the residuals of none of the price series suffer from the ARCH effect. The Nyblom stability test checks for a structural break in price volatility; the results indicate that there is no structural break in any of the series. The sign bias test checks whether the conditional volatility model is specified correctly; the results show that all the models were correctly specified. All the test results indicate that the models built for the data are adequate and precise.

Conclusions and implications

The COVID-19 pandemic and the lockdown severely reduced the quantities traded of all the commodities, increasing their wholesale prices substantially, but the increase varied by market. The prices of onions and tomatoes in Delhi and potatoes in Mumbai rose high in the first phase, and the prices continued to rise in the second phase, but the rising trend started tapering off gradually after the government began easing the lockdown on 31 May 2020 and vanished soon after. The lockdown also impacted price volatility – more so during its first phase – and the mean and variance of commodity prices heterogeneously across commodities and markets.

This paper considers perishable food commodities that need to be transferred immediately to market centres or consumers, or stored, or processed, or converted into value-added products to avoid the risk of post-harvest farm-level loss. Investing in supply chain infrastructure – including transportation, storage, and processing – and strengthening institutions like cooperatives and contract farming will link farmers to markets. The evidence in this paper – based on long series data encompassing the periods before and after the lockdown – can be used to frame public policy that directly impacts supply chains and farmer incomes. The pandemic has caused people to panic, and they may stockpile commodities and increase price volatility. Policymakers need to investigate this possibility.

The pandemic may have longer-term consequences; research is required to anticipate these.

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Appendix

Table A1 Shapiro–Wilk test for testing the normality of series

Onions				
	Price		Arrivals	
Market	Test statistics	p-value	Test statistics	p-value
Delhi	0.709	<0.001	0.981	<0.001
Mumbai	0.681	<0.001	0.985	<0.001
Bengaluru	0.575	<0.001	0.817	<0.001
Potatoes				
Delhi	0.939	<0.001	0.974	<0.001
Mumbai	0.977	<0.001	0.994	<0.001
Bengaluru	0.988	<0.001	0.753	<0.001
Tomatoes				
Delhi	0.893	<0.001	0.984	<0.001
Mumbai	0.876	<0.001	0.974	<0.001

Table A2 Model adequacy tests

	Delhi		Mumbai		Bengaluru	
	statistic	p-value	statistic	p-value	statistic	p-value
Onions						
Weighted Ljung-Box Test of Standardized Residuals						
Lag[1]	0.515	0.472	2.732	0.098	1.879	0.170
Lag[5]	2.291	0.874	4.094	0.052	3.041	0.446
Lag[9]	4.475	0.577	6.357	0.202	5.041	0.444
Weighted Ljung-Box Test of Standardized Squared Residuals						
Lag[1]	0.075	0.783	0.302	0.582	0.0026	0.959
Lag[5]	0.287	0.985	0.613	0.938	0.878	0.886
Lag[9]	1.190	0.976	1.483	0.956	1.522	0.953
ARCH LM test (H_0: No ARCH effect)						
Lag[3]	0.045	0.831	0.013	0.906	0.624	0.429
Lag[5]	0.286	0.943	0.554	0.867	0.873	0.770
Lag[7]	1.264	0.867	1.297	0.861	1.174	0.880
Nyblom Stability Test (H_0: There is no structural change)						
Joint Statistic	2.599		2.926		1.382	
Sign Bias Test (H_0: No misspecification of conditional volatility models)						
Sign Bias	1.023	0.306	0.009	0.992	1.059	0.317
Negative Sign Bias	0.954	0.339	0.590	0.555	0.496	0.619
Positive Sign Bias	1.004	0.315	1.334	0.182	0.072	0.942
Joint Effect	2.246	0.522	2.472	0.480	5.355	0.147

	Delhi		Mumbai		Bengaluru	
	statistic	p-value	statistic	p-value	statistic	p-value
Potatoes						
Weighted Ljung-Box Test of Standardized Residuals						
Lag[1]	0.302	0.582	1.331	0.248	0.081	0.775
Lag[5]	2.291	0.874	3.023	0.457	2.016	0.955
Lag[9]	2.644	0.937	4.435	0.587	6.585	0.173
Weighted Ljung-Box Test of Standardized Squared Residuals						
Lag[1]	0.094	0.759	3.763	0.052	2.36	0.124
Lag[5]	0.348	0.978	3.978	0.256	2.94	0.417
Lag[9]	0.602	0.997	4.096	0.572	3.96	0.595
ARCH LM test (H_0: No ARCH effect)						
Lag[3]	0.129	0.718	0.032	0.857	0.461	0.497
Lag[5]	0.337	0.930	0.104	0.986	1.045	0.719
Lag[7]	0.486	0.979	0.164	0.998	1.896	0.739
Nyblom Stability Test (H_0: There is no structural change)						
Joint Statistic	2.245		2.206		1.592	
Sign Bias Test (H_0: No misspecification of conditional volatility models)						
Sign Bias	0.929	0.352	1.110	0.267	0.248	0.804
Negative Sign Bias	0.394	0.693	0.821	0.411	0.295	0.768
Positive Sign Bias	0.411	0.681	1.692	0.090	0.343	0.731
Joint Effect	1.747	0.626	3.546	0.314	0.531	0.912
Tomatoes						
Weighted Ljung-Box Test of Standardized Residuals						
Lag[1]	0.132	0.715	0.347	0.555		
Lag[5]	2.423	0.817	1.482	0.998		
Lag[9]	4.963	0.462	2.644	0.937		
Weighted Ljung-Box Test of Standardized Squared Residuals						
Lag[1]	0.538	0.463	0.248	0.618		
Lag[5]	0.866	0.889	0.482	0.960		
Lag[9]	1.188	0.977	0.911	0.989		
ARCH LM test (H_0: No ARCH effect)						
Lag[3]	0.161	0.688	0.157	0.691		
Lag[5]	0.190	0.967	0.376	0.919		
Lag[7]	0.334	0.990	0.612	0.967		
Nyblom Stability Test (H_0: There is no structural change)						
Joint Statistic	2.558		1.1917			
Sign Bias Test (H_0: No misspecification of conditional volatility models)						
Sign Bias	1.179	0.238	1.239	0.215		
Negative Sign Bias	1.229	0.219	0.194	0.846		
Positive Sign Bias	0.601	0.547	0.367	0.713		
Joint Effect	2.740	0.433	1.671	0.643		