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Revisiting India's Pulse Supply Response for Asymmetry: A Case Study on Chickpea in Madhya Pradesh

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ABSTRACT

The importance of an accurate assessment of India's pulse supply responsiveness cannot be overstated, especially given the vital role of pulses in agricultural sustainability and human well-being, yet a dismal per capita availability figure; hence, the case for comprehensively revisiting pulse supply responsiveness for asymmetry. Recent econometric research has prioritized the analysis of non-stationarity alongside nonlinearity, acknowledging the ubiquitous influence of asymmetry and its intrinsic value. The present study examines asymmetry in the supply response of chickpea, a representative pulse crop, in Madhya Pradesh, a leading pulse-producing state in India, from 1970–71 to 2015–16, when the pulse sector lay virtually dormant. It detects the presence of asymmetry in the area and yield responses to price and selected non-price variables through ECM-based estimations of the ARDL and NARDL models, each with two specifications, in the context of dynamic panel data analysis through the PMG estimator. To the authors' knowledge, this is the first NARDL-based supply response study about Indian agriculture – some applications exist that do not include the price variable; thus, they do not fit squarely within the framework of supply response studies. The NARDL estimation results indicate that the percentages of SR/LR asymmetric responses per model to the decomposed variables (partial sum processes of positive and negative changes) across the area and yield response models range from 57% to 75%. These findings offer fresh perspectives on pulse supply responsiveness, which could significantly inform policymaking in this domain.

Keywords: Supply Response, Chickpea, Asymmetry, Panel Data, ARDL ECM-based Estimation, Panel NARDL ECM-based Estimation

JEL codes: Q11, Q12, Q13, Q18

I

INTRODUCTION

India's agricultural sector is of paramount importance to the Indian economy. Not only do about 55% of the country's population depend on it as the primary source of their livelihood (IBEF, 2023), but also its share of the workforce, which has been on the increase since 2018–19, stands at 45.5% Over the period 2019–23, this sector grew at a compound annual growth of 4%, accounting for about 15% of the Gross Value Added for 2023 (NABARD, 2023). Foodgrain production reached a record high of about 330 million tonnes in 2023 (GoI, 2024); however, domestic demand exceeds production, so India relies on food imports, including pulses.

India's pulse sector lay dormant from 1950–51 to 2009–10, with annual production mostly between 10 and 15 million tonnes. Boosted by the ongoing National Food Security Mission (NFSM), it rose moderately over the following quinquennium but dipped to about 16 million in 2015–16. A subsequent surge saw production exceed 23 million tonnes annually, except for 2018–19, soaring to a record 27-plus million in 2021–22. Nevertheless, it declined over the next two years to about 26.1 and 24.5

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million, with chickpea production declining from about 13.5 to 11.6 million tonnes (GoI, 2024).

Considering the contribution of pulses to food security and nutrition, there is a need for a better understanding of the quantitative dimensions of pulse supply response. The present study analyses chickpea production response in the leading pulse-producing state of Madhya Pradesh for the period 1970–71 to 2015–16 when pulse production remained sluggish. Its specific objectives are to: (i) study the area and yield responses of chickpea to price and selected non-price variables, (ii) estimate the short-run and long-run elasticities of the area and yield responses, and (iii) check these responses for symmetry.

II

LITERATURE REVIEW

Past studies on pulse supply response in India ignore asymmetric relationships, implicitly assuming supply response to be symmetric or reversible. Economists have long known that many macroeconomic variables and processes are nonlinear (Shin et al., 2013). However, early applications of the irreversibility concept in agricultural supply response are limited. The few existing studies (e.g., Jaforullah, 1993; Traill et al., 1978) seem to reveal asymmetric area responses to price changes, with acreage responding more to a price rise than a price fall (Mamingi, 1997). Recently, the modelling of asymmetry has been engaging the increasing attention of researchers in different domains, with applications in agriculture examining the effects of non-price factors on crop yield or production.

Agricultural supply response has conventionally relied on the seminal Nerlove (1958) model, but more recent work has used the cointegration and error correction framework. Investigating the applicability of the error correction specification to agricultural supply modelling, Hallam and Zanoli (1993) document its superiority over the Nerlovian partial adjustment model. Examples of its use in modelling supply response in Indian agriculture include Paltasingh and Goyari (2013) and Savadatti (2018). The error correction model (ECM) is derivable as a simple reparameterization of a general autoregressive distributed lag (ARDL) model (Hendry et al., 1984).

2.1 The Nonlinear Autoregressive Distributed Lag (NARDL) Model

Shin et al.'s (2014) NARDL model is an asymmetric extension of the ARDL model developed by Pesaran and Shin (1998, as cited in Shin et al., 2013) and Pesaran et al. (2001), which has proven highly influential as the cornerstone of several significant methodological extensions (Cho et al., 2020). The NARDL model captures short- and long-run asymmetric effects via decomposing the explanatory variables into partial sum processes of positive and negative changes, providing a more nuanced understanding of how variables interact over time. The formulation of the model builds around the following asymmetric long-run regression between scalar I (1) variables y_t and x_t:

$$y_t = \beta^+ x_t^+ + \beta^- x_t^- + u_t, \qquad \text{…. (1)}$$

$$\Delta x_t = \quad v_t, \qquad \text{…. (2)}$$

where x_t^+ and x_t^- represent the partial sum processes of positive and negative changes in x_t, which is decomposed as $x_t = x_0$ (i.e., random initial value) $+ x_t^+ + x_t^-$:

$$x_t^+ = \sum_{j=1}^{t} \Delta x_j^+ = \sum_{j=1}^{t} max\,(\Delta x_j, 0), \qquad \text{…. (3)}$$

$$x_t^- = \sum_{j=1}^{t} \Delta x_j^- = \sum_{j=1}^{t} min\,(\Delta x_j, 0). \qquad \text{…. (4)}$$

This subsection excludes full representation of the model due to space limitations. Formulating the asymmetric model from the symmetric one is straightforward, as seen in Eqs (5) and (8) below.

The NARDL model admits three general forms of asymmetry – long-run or reaction asymmetry, impact asymmetry and adjustment asymmetry associated respectively with inequalities of β^+ and β^-, the coefficients of Δx_t^+ and Δx_t^-, and the patterns of adjustment traced by the dynamic multipliers. As such, asymmetries in the adjustment patterns might be observed even with little evidence of the other kinds of asymmetry. The model's desirability, as the authors note, is threefold – the single-step estimation of the ECM, with a better performance in small samples, particularly regarding the cointegration tests' power; the simultaneous estimation of both long- and short-run asymmetries in a tractable and straightforward manner, with simple testing for symmetry restrictions; and the intuitive and easy evaluation of the transition from the short to the long run.

Turning to the application of the NARDL model in agriculture, three studies, all in a time series context, are briefly reviewed here. Abbas et al. (2022) investigate the impacts of average maximum and minimum temperatures, rainfall, total area sown, and total irrigated and unirrigated acreages on the production of rice in the Central, Southern and Western regions of Punjab, Pakistan, using both ARDL and NARDL models. The NARDL analysis reveals asymmetric effects of temperature, rainfall and total area sown. Addresssing selected principal crops of Odisha, including gram, Senapati (2022) estimates the overall effect of rainfall, temperature, irrigation, ground frost frequency, and crop evapotranspiration on their yields for the period 1950–2017, with rainfall as the chief concern. The findings indicate an overall asymmetric effect of rainfall on the yield but a minimal role of the other variables. In the case of gram, the implication is that whereas the yield is unresponsive to rainfall increases, a 1% decrease reduces acreage allocated to the crop by about 0.81%, ceteris paribus, in both the short and long runs. The third study, by Mujtaba et al. (2023), investigates the asymmetric response of India's rice, wheat, and maize yields for the period 1980–2017 to temperature, rainfall, CO_2 emissions, and fertilizer consumption. The empirical findings support asymmetry in the short and long runs, indicating statistically distinct impacts of positive and negative changes in the relevant variables, with diverse impacts of temperature, CO_2 emissions and fertilizer consumption.

Although the above NARDL applications do not strictly constitute supply response studies, their findings suggest the presence of asymmetry in pulse supply response. The present study bridges this research gap.

III

METHODOLOGY

This study focuses on Madhya Pradesh, whose contribution to the area and production of chickpea in India over the study period (1970–71 to 2015–16) averages 32.30% and 34.93%, respectively. Data sources include the ICRISAT district-level database, annual publications of 'Farm Harvest Prices of Principal Crops in India' from the Directorate of Economics and Statistics, Ministry of Agriculture and Farmers Welfare, the Economic and Political Weekly Research Foundation (EPWRF) India Time Series dataset on Price Indices, and the India Water Resources Information System portal (http://www.indiawris.gov.in). The study covers 29 districts and uses data on area, yield and farm harvest price (FHP) of pigeon pea, gross cropped area, gross irrigated area, total fertilizer (NPK) consumption, monthly rainfall and temperature. The EPWRF's CPI-AL data, utilized to construct relative price and risk, represent the average of CPI-AL values for January and February in a given year as farmers generally dispose of their produce within six to eight weeks of the commencement of the harvest season (Durga & Swaminathan, 2018). Furthermore, the study captures the effects of government intervention on the NFSM post-2010 using a binary variable, which is assumed to impact area or yield in the short run but not to affect their equilibrium paths.

The reference period for the study, 1970–71 to 2015–16 (46 years), reveals many missing values for FHP and rainfall data. Filled in missing price values constitute either borrowed data or values imputed using the exponential moving average approach. However, districts with over 20% of FHP data missing for the study period or with such missing values for five or more consecutive years ending 2018 do not form part of the study.

3.1 Conceptual Models

Each area and yield response analysis employs two ARDL and two NARDL model specifications (I and II). The reason for testing two different specifications is to accommodate the possibility that infrastructure and technology variables in the same model may face multi-collinearity issues. The NARDL models include the same underlying variables as the ARDL models and, except for infrastructure, technology and irrigation, owing to their predominantly positive growth rates, decompose each into partial sum processes of positive and negative changes.

3.1.1 The ARDL Area Response Models

This study formulates the ARDL area response model I as

$$\Delta ln(cph)_{i,t} = \beta_{0i} + \beta_{1i}\, ln(cph)_{i,t-1} + \beta_{2i}\, ln(rfhp)_{i,t-1} + \beta_{3i}\, ln(\%gia)_{i,t-1} + \beta_{4i}\, ln(r\_ps)_{i,t-1} + \beta_{5i}\, ln(cvrr)_{i,t-1} + \sum_{j=1}^{N1} \lambda_{ij}\, \Delta ln(cph)_{i,t-j} + \sum_{j=0}^{N2} a_{ij}\, \Delta ln(rfhp)_{i,t-j} + \sum_{j=0}^{N3} b_{ij}\, \Delta ln(\%gia)_{i,t-j} + \sum_{j=0}^{N4} c_{ij}\, \Delta ln(r\_ps)_{i,t-j} + \sum_{j=0}^{N5} d_{ij}\, \Delta ln(cvrr)_{i,t-j} + D\_nfsm_t + \mu_i + \varepsilon_{it}, \quad \text{.... (5)}$$

where the symbols utilized, other than the parameters to be estimated, are defined as follows:

Δ and ln ≡ the forward difference operator and the natural logarithm

i and t ≡ subscripts for the cross-section and production period to which a variable refers, t differing between variables: [$i = 1, 2, \ldots, N$; $t = 1, 2, \ldots, T$]

$(cph)_{i,t}$ ≡ chickpea acreage in the current period in '000 hectares

$(rfhp)_{i,t}$ ≡ an index of the previous period's FHP of chickpea relative to the CPI-AL:

$$\left[\frac{\text{The previous period's FHP in Rs/qtl}}{\text{The previous period's CPI−AL average for Feb−Mar}} \times 100\right]$$

$(\%gia)_{i,t}$ ≡ the previous period's percent gross irrigated area under all crops as a proxy for infrastructure: [$\frac{\text{GIA}}{\text{GCA}} \times 100$],

$(r\_ps)_{i,t}$ ≡ the pre-sowing rainfall in mm: June – September

$(cvrr)_{i,t}$ ≡ coefficient of variation of the relative gross returns from chickpea relative to the CPI-AL over the three preceding years as an index of the risk associated with its profitability:

[Relative gross returns $= \frac{\text{Yield (kg/ha)} \times \frac{\text{FHP (Rs/q)}}{100}}{\text{CPI−AL (Feb−Mar avg.)}} \times 100 =$ Relative FHP $\times \frac{\text{Yield (kg/ha)}}{100}$]

$N^{\text{superscript}}$ ≡ the optimal lag order

D_nfsm_t ≡ a dummy variable for government intervention in respect of NFSM post-2010 [D_nfsm_t equals 0 when $t < 2010$ and 1 when $t \geq 2010$]

μ_i and $\varepsilon_{i,t}$ ≡ the group-specific effect and the error term

In this 'double-log' functional form, the coefficients of the differenced terms represent the short-run elasticities. The corresponding long-run slope coefficients (elasticities) are obtained by dividing the coefficients of the lagged levels of the long-run forcing variables by that of the lagged dependent variable – in the long run, all the differenced terms of the long-run forcing variables equal zero.

The error correction reparameterization of eq. (5) is:

$$\Delta ln(cph)_{i,t} = \delta_i \upsilon_{i,t-1} + \sum_{j=1}^{N1} \lambda_{ij}\, \Delta ln(cph)_{i,t-j} + \sum_{j=0}^{N2} a_{ij}\, \Delta ln(rfhp)_{i,t-j} + \sum_{j=0}^{N3} b_{ij}\, \Delta ln(\%gia)_{i,t-j} + \sum_{j=0}^{N4} c_{ij}\, \Delta ln(r\_ps)_{i,t-j} + \sum_{j=0}^{N5} d_{ij}\, \Delta ln(cvrr)_{i,t-j} + D\_nfsm_t + \mu_i + \varepsilon_{it}, \quad \ldots.(6)$$

where

$$\upsilon_{i,t-1} = ln(cph)_{i,t-1} - \phi_{0i} - \phi_{1i}\, ln(rfhp)_{i,t-1} - \phi_{2i}\, ln(\%gia)_{i,t-1} - \phi_{3i}\, ln(r\_ps)_{i,t-1} - \phi_{4i}\, ln(cvrr)_{i,t-1} \quad \ldots.\ (7)$$

is the error correction term capturing the long-run cointegration relationship (which holds at equilibrium) and δ_i, the speed of adjustment (error correction) parameter. By mapping the coefficients in eq. (6) algebraically to the corresponding ones in eq. (5) it can be seen that $\delta_i = \beta_{1i}$, $\phi_{0i} = -\beta_{0i}/\beta_{1i}$, $\phi_{1i} = -\beta_{2i}/\beta_{1i}$, $\phi_{2i} = -\beta_{3i}/\beta_{1i}$, $\phi_{3i} = -\beta_{4i}/\beta_{1i}$, and $\phi_{4i} = -\beta_{5i}/\beta_{1i}$.

The formulation of the ARDL area response model II is identical but replaces $ln(\%gia)_{i,t}$ with $ln(npk\_ha)_{i,t}$, which denotes the previous period's total fertilizer consumption per hectare of the gross cropped area as a proxy for technology.

3.1.2 The NARDL Area Response Models

The formulation of the NARDL area response model I is:

$$\Delta ln(cph)_{i,t} = \beta_{0i} + \beta_{1i}\, ln(cph)_{i,t-1} + \beta_{2i}^{+}\, ln(rfhp)_{i,t-1}^{+} + \beta_{2i}^{-}\, ln(rfhp)_{i,t-1}^{-} + \beta_{3i}\, ln(\%gia)_{i,t-1} + \beta_{4i}^{+}\, ln(r\_ps)_{i,t-1}^{+} + \beta_{4i}^{-}\, ln(r\_ps)_{i,t-1}^{-} + \beta_{5i}^{+}\, ln(cvrr)_{i,t-1}^{+} + \beta_{5i}^{-}\, ln(cvrr)_{i,t-1}^{-} + \sum_{j=1}^{N1} \lambda_{ij}\, \Delta ln(cph)_{i,t-j} + \sum_{j=0}^{N2} [a_{ij}^{+}\, \Delta ln(rfhp)_{i,t-j}^{+} + a_{ij}^{-}\, \Delta ln(rfhp)_{i,t-j}^{-}] + \sum_{j=1}^{N3} b_{ij}\, \Delta ln(\%gia)_{i,t-j} + \sum_{j=0}^{N4} [c_{ij}^{+}\, \Delta ln(r\_ps)_{i,t-j}^{+} + c_{ij}^{-}\, \Delta ln(r\_ps)_{i,t-j}^{-}] + \sum_{j=0}^{N5} [d_{ij}^{+}\, \Delta ln(cvrr)_{i,t-j}^{+} + d_{ij}^{-}\, \Delta ln(cvrr)_{i,t-j}^{-}] + D\_nfsm_t + \mu_i + \varepsilon_{it}, \quad \ldots.(8)$$

where the variable superscripts '$+$' and '$-$' denote the partial sum decompositions of the variable of concern, say $`\mathrm{var}'_{it}$, into positive and negative changes, that is

$$`\mathrm{var}'^{+}_{it} = \sum_{j=1}^{t} \Delta`\mathrm{var}'^{+}_{ij} = \sum_{j=1}^{t} max\,(\Delta`\mathrm{var}'_{ij}, 0), \quad \ldots.\ (9)$$

$$`\mathrm{var}'^{+}_{it} = \sum_{j=1}^{t} \Delta`\mathrm{var}'^{+}_{ij} = \sum_{j=1}^{t} min\,(\Delta`\mathrm{var}'_{ij}, 0); \quad \ldots.(10)$$

the parameter superscripts differentiate between the respective parameters for these partial sum processes; and the rest of the symbols represent as in eq. (5). This NARDL model I yields the short- and long-run elasticities similarly to the symmetric model. For instance, the short-run elasticities concerning the positive and negative price shocks are a_{ij}^{+} and a_{ij}^{-}, while the respective long-run elasticities are $-\beta_{2i}^{+}/\beta_{1i}$ and $-\beta_{2i}^{-}/\beta_{1i}$.

The reformulation of eq. (8) in the error correction representation yields:

$$\Delta ln(cph)_{i,t} = \tau_i \xi_{i,t-1} + \sum_{j=1}^{N1} \lambda_{ij}\, \Delta ln(cph)_{i,t-j} + \sum_{j=0}^{N2} [a_{ij}^{+}\, \Delta ln(rfhp)_{i,t-j}^{+} + a_{ij}^{-}\, \Delta ln(rfhp)_{i,t-j}^{-}] + \sum_{j=1}^{N3} b_{ij}\, \Delta ln(\%gia)_{i,t-j} + \sum_{j=0}^{N4} [c_{ij}^{+}\, \Delta ln(r\_ps)_{i,t-j}^{+} + c_{ij}^{-}\, \Delta ln(r\_ps)_{i,t-j}^{-}] + \sum_{j=0}^{N5} [d_{ij}^{+}\, \Delta ln(cvrr)_{i,t-j}^{+} + d_{ij}^{-}\, \Delta ln(cvrr)_{i,t-j}^{-}] + D\_nfsm_t + \mu_i + \varepsilon_{it}, \quad ....(11)$$

where, analogous to $\delta_i v_{i,t-1}$ in eq. (6),

$$\xi_{i,t-1} = ln(cph)_{i,t-1} - \sigma_{0i} - \sigma_{1i}^{+}\, ln(rfhp)_{i,t-1}^{+} - \sigma_{1i}^{-}\, ln(rfhp)_{i,t-1}^{-} - \sigma_{2i}\, ln(\%gia)_{i,t-1} - \sigma_{3i}^{+}\, ln(r\_ps)_{i,t-1}^{+} - \sigma_{3i}^{-}\, ln(r\_ps)_{i,t-1}^{-} - \sigma_{4i}^{+}\, ln(cvrr)_{i,t-1}^{+} - \sigma_{4i}^{-}\, ln(cvrr)_{i,t-1}^{-} \quad .... (12)$$

is the error correction term, and τ_i, the speed of adjustment parameter.

In the otherwise identical NARDL area response model II, $ln(npk\_ha)_{i,t}$ replaces $ln(\%gia)_{i,t}$.

3.1.3 The ARDL and NARDL Yield Response Models

The ARDL and NARDL yield response models are formulated and reparameterized into ECMs analogously to the respective area response models. The yield response variables include $(rfhp)_{i,t}$ and D_nfsm_t as defined earlier, and as for the rest of the symbols, leaving the parameters aside, their denotation is as follows:

$(cpy)_{i,t}$ ≡ chickpea yield in the current period in kg/ha

$(\%gia)_{i,t}$ ≡ the current period's percent gross irrigated area under all crops as a proxy for infrastructure: $[\frac{\text{GIA}}{\text{GCA}} \times 100]$

$(\%cpia)_{i,t}$ ≡ the current period's percent irrigated area under chickpea as a measure of irrigation:

$$[\frac{\text{Chickpea irrigated acreage in the current period ('000 ha)}}{\text{Total chickpea acreage in the current period ('000 ha)}} \times 100]$$

$(r\_br)_{i,t}$ ≡ the current period's rainfall in mm during branching: October – November

$(r\_pf)_{i,t}$ ≡ the current period's rainfall in mm during pod filling: January – February

$(t\_dec)_{i,t}$ ≡ the maximum temperature in ℃ during December

$(t\_jan)_{i,t}$ ≡ the maximum temperature in °C during January
υ_i and ϵ_{it} ≡ the group-specific effect and the error term

3.2 Estimation Technique

The study uses the LLC (Levin et al., 2002), HT (Harris & Tzavalis, 1999), Breitung (Breitung & Das, 2005), IPS (Im et al., 2003), ADF (Choi, 2001) and Hadri LM (Hadri, 2000) panel tests for the unit root analysis; the *forval* command to automatically generate the district-wise optimal lag orders through the Bayesian information criterion (BIC) in order to constitute the optimal lag order for the panel composed of the most common number of lags for each variable of concern across the cross-sections; the residual-based Kao (1999) test to confirm cointegration among the variables; and the statistical software package Stata 16.1 to estimate the models of concern through the PMG estimator – widely adopted in the ARDL framework, having been assessed by many authors as superior to the MG estimator (e.g., Abbasi et al., 2022); Alamgir & Amin, 2021; Odugbesan et al., 2021; Salisu & Isah, 2017).

IV

RESULTS AND DISCUSSION

4.1 Preliminary Analyses

Table 1 reports descriptive statistics of concern on the area and yield response variables. While the ARDL approach to cointegration yields valid results regardless of

TABLE 1: DESCRIPTIVE STATISTICS ON AREA AND YIELD RESPONSE VARIABLES

Variable	No. of Obs.	Mean	Std. Dev.	Min.	Max.
(1)	(2)	(3)	(4)	(5)	(6)
Area Response					
($\boldsymbol{cph}$)	1334	59.74	42.34	1.10	229.00
($\boldsymbol{rfhp}$)	1334	64.22	15.60	32.30	132.10
(%$\boldsymbol{gia}$)	1334	22.00	16.13	0.40	75.64
($\boldsymbol{npk\_ha}$)	1334	34.40	34.23	0.18	221.18
($\boldsymbol{r\_ps}$)	1334	928.85	302.89	180.50	2230.70
($\boldsymbol{cvrr}$)	1334	20.22	11.98	0.34	86.43
Yield Response					
($\boldsymbol{cpy}$)	1334	760.77	304.51	107.69	2828.83
($\boldsymbol{rfhp}$)	1334	64.22	15.60	32.30	132.10
(%$\boldsymbol{gia}$)	1334	22.78	16.36	0.53	75.64
($\boldsymbol{npk\_ha}$)	1334	36.10	34.96	0.30	221.18
(%$\boldsymbol{cpia}$)	1334	27.52	24.69	0.00	146.30
($\boldsymbol{r\_br}$)	1334	39.90	51.33	0.00	735.80
($\boldsymbol{r\_pf}$)	1334	22.38	31.59	0.00	194.40
($\boldsymbol{t\_dec}$)	1334	26.58	1.70	20.88	32.32
($\boldsymbol{t\_jan}$)	1334	25.18	2.10	20.70	35.22

whether the order of integration of the underlying variables is one, zero, or a combination of both (Pesaran et al., 2001), it is still necessary to ascertain that no I (2) variable is involved, as its presence can render the regression of concern spurious (Qamruzzaman & Jianguo, 2018). All the variables of concern are either stationary in levels or are rendered stationary with first-order differencing at the 1% significance level, except for the area response variable $ln(\%gia)_{i,t}$ under the Hadri LM test, its first difference proving stationary at the 10% level. The district-wise optimal number of the autoregressive and distributed lags for the area and yield response models show that (1, 0, 0, 0, 0) and (1, 0, 0, 0, 0, 0, 0, 0) are the orders consisting of the most common number of lags for each variable of concern across the cross-sections for the symmetric and asymmetric area response models, respectively. Such lag orders for the pertinent yield response models are (1, 0, 0, 0, 0, 0, 0, 0) and (1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0). These lag orders serve as the optimal lag orders for the respective panel data analyses. Table 2 depicts the results of the Kao cointegration tests for the area and yield response

TABLE 2: PANEL COINTEGRATION TEST RESULTS

KAO Test	Area Response				Yield Response			
	Statistic	p-value	Statistic	p-value	Statistic	p-value	Statistic	p-value
(1)	(2)		(3)		(4)		(5)	
ARDL Specification	Model I		Model II		Model I		Model II	
Modified Dickey-Fuller t	-8.405	0.000	-5.979	0.000	-27.854	0.000	-27.840	0.000
Dickey-Fuller t	-7.143	0.000	-5.214	0.000	-17.579	0.000	-17.644	0.000
Augmented Dickey-Fuller t	-1.443	0.074	-1.076	0.141	-10.634	0.000	-10.775	0.000
Unadjusted modified Dickey-Fuller t	-17.383	0.000	-12.177	0.000	-40.249	0.000	-40.416	0.000
Unadjusted Dickey-Fuller t	-9.693	0.000	-7.301	0.000	-18.980	0.000	-19.071	0.000
NARDL Specification	Model I		Model II		Model I		Model II	
Modified Dickey-Fuller t	-5.362	0.000	-2.747	0.003	-29.486	0.000	-29.293	0.000
Dickey-Fuller t	-5.462	0.000	-3.224	0.001	-18.279	0.000	-18.363	0.000
Augmented Dickey-Fuller t	0.220	0.413	0.710	0.239	-11.381	0.000	-11.569	0.000
Unadjusted modified Dickey-Fuller t	18.164	0.000	-12.638	0.000	-41.557	0.000	-41.991	0.000
Unadjusted Dickey-Fuller t	-9.897	0.000	-7.455	0.000	-19.547	0.000	-19.726	0.000

models. All the relevant statistics resoundingly reject the null of no cointegration, excluding the ADF test statistics for the area response models, for which this test rejects the null only in the ARDL model I and that, too, just at the 10% level, but this takes nothing away from the results of the other tests. The ADF test does not generally perform creditably and its empirical distribution can deviate significantly from the theoretical standard normal distribution (Barbieri, 2008).

4.2 ARDL Analysis of Area Response

As depicted in Table 3, both models yield long-run responses to all the variables other than risk that are positive and significant at the 1 per cent level, indicating a favourable and normal consequence on planting decisions. The elasticity estimates from model I indicate that chickpea acreage increases by about 0.57 per cent and 0.42 per cent, respectively, for every 1 per cent increase in the relative farm harvest price and pre-sowing rainfall, ceteris paribus, and vice versa; the corresponding figures for

TABLE 3: PMG ESTIMATES OF PANEL ARDL AREA RESPONSE MODELS

Model I				**Model II**			
Variable	Coeff	Variable	Coeff	Variable	Coeff	Variable	Coeff
Long Run		Short Run		Long Run		Short Run	
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
		$\_\_ec$	-0.2832***[b]			$\_\_ec$	-0.2893***[b]
			(0.0438)				(0.0477)
$\boldsymbol{ln(rfhp)}$	0.5679***	$\Delta ln(rfhp)$	-0.1105**	$ln(rfhp)$	0.4086***	$\Delta ln(rfhp)$	-0.0851**
	(0.1210)		(0.0447)		(0.1092)		(0.0412)
$\boldsymbol{ln(\%gia)}$	0.1672***	$\Delta ln(\%gia)$	-0.1172*	$ln(npk\_ha)$	0.1889***	$\Delta ln(npk\_ha)$	0.0214
	(0.0421)		(0.0683)		(0.0267)		(0.0288)
$\boldsymbol{ln(r\_ps)}$	0.4229***	$\Delta ln(r\_ps)$	-0.0150	$ln(r\_ps)$	0.2767***	$\Delta ln(r\_ps)$	0.0286
	(0.0987)		(0.0159)		(0.0770)		(0.0185)
$\boldsymbol{ln(cvrr)}$	-0.0319	$\Delta ln(cvrr)$	0.0389***	$ln(cvrr)$	-0.0151	$\Delta ln(cvrr)$	0.0338***
	(0.0367)		(0.0105)		(0.0323)		(0.0099)
		D_nfsm	0.0482*			D_nfsm	0.0352
			(0.0254)				(0.0261)
		_cons	-0.4661***			$\_cons$	-0.0287
			(0.0796)				(0.0492)
No. of observations = 1305 / No. of cross sections = 29				No. of observations = 1305 / No. of cross sections = 29			
Log Likelihood = 279.8629				Log Likelihood = 263.6043			

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$ (Figures in parentheses are standard errors).
[b] No. of yrs, say N, for adjustment to within 5% of complete adjustment = 9 [obtained from the relationship: $(1 - |Coeff|)^N < 0.05$].

model II are 0.41% and 0.28%. The infrastructure and technology factors imply that all else equal, a 1% increase in these variables induces acreage increases of 0.17% and 0.19%, respectively, and vice versa. However, the risk factor proves insignificant.

The quasi-identical averaged estimates of the error correction coefficient from both models are properly signed (negative) and highly significant (see Table 3, cols. 4 and 8), with a mean value of about -0.29, implying nine years for adjustment to within 5% of complete adjustment. In the short run, the response to price emerges significantly negative. In this regard, one might conjecture that farmers have a relatively fixed demand for money in the short run, allocating only enough land to chickpea to generate the desired income and meet their on-farm consumption requirement, with the rest dedicated to the subsistence crop – over time, they tend to respond positively as the shocks persist. Alternatively, the negative response might be ascribable to the imposition of symmetry in the underlying relationship, jeopardizing the identification of the long-run relationship and resulting in spurious dynamic responses (Shin et al., 2013).

Short-run responses elicited by the infrastructure factor (Model I) and the risk factor under both models are also contrary to expectations; the former reverses with time while the risk-incurring tendency dies. The NFSM dummy claims significance only under Model I, indicating that government intervention concerning NFSM post-2010 increases chickpea acreage by about 5%, all else equal.

4.3 NARDL Analysis of Area Response

The positive as well as negative shocks to price and rainfall all evoke positive long-run responses (i.e., in the direction of the shock) under both models (see Table 4), which prove significant at the conventional levels (1% and 5%). For model I, the price estimates indicate that ceteris paribus, a 1% positive price change increases acreage by about 0.74%, whereas a 1 % negative change decreases it by about 0.53%. The Wald

TABLE 4: PMG ESTIMATES OF PANEL NARDL AREA RESPONSE MODELS

Model I				Model II			
Variable	**Coeff**	**Variable**	**Coeff**	**Variable**	**Coeff**	**Variable**	**Coeff**
Long Run		**Short Run**		**Long Run**		**Short Run**	
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
		$\_\_ec$	-0.3105***[b] (0.0465)			$\_\_ec$	-0.3039***[d] (0.0474)
$\boldsymbol{ln(rfhp)^+}$	0.7370*** (0.1436)	$\Delta ln(rfhp)^+$	-0.1501 (0.0973)	$ln(rfhp)^+$	0.3813*** (0.1422)	$\Delta ln(rfhp)^+$	-0.0229 (0.0854)
$\boldsymbol{ln(rfhp)^-}$	0.5285*** (0.1581)	$\Delta ln(rfhp)^-$	-0.1130 (0.0738)	$ln(rfhp)^-$	0.3734*** (0.1382)	$\Delta ln(rfhp)^-$	-0.1484** (0.0647)
$\boldsymbol{ln(\%gia)}$	0.2331*** (0.0537)	$\Delta ln(\%gia)$	-0.1408* (0.0771)	$ln(npk\_ha)$	0.1309*** (0.0390)	$\Delta ln(npk\_ha)$	0.0419 (0.0332)
$\boldsymbol{ln(r\_ps)^+}$	0.3814*** (0.0914)	$\Delta ln(r\_ps)^+$	0.0218 (0.0400)	$ln(r\_ps)^+$	0.3093*** (0.0815)	$\Delta ln(r\_ps)^+$	0.0729** (0.0371)
$\boldsymbol{ln(r\_ps)^-}$	0.3384*** (0.0899)	$\Delta ln(r\_ps)^-$	-0.0446 (0.0393)	$ln(r\_ps)^-$	0.2242** (0.0764)	$\Delta ln(r\_ps)^-$	-0.0141 (0.0432)
$\boldsymbol{ln(cvrr)^+}$	-0.0908** (0.0382)	$\Delta ln(cvrr)^+$	0.0637** (0.0257)	$ln(cvrr)^+$	-0.0491 (0.0371)	$\Delta ln(cvrr)^+$	0.0425* (0.0227)
$\boldsymbol{ln(cvrr)^-}$	0.0476 (0.0360)	$\Delta ln(cvrr)^-$	0.0185 (0.0169)	$ln(cvrr)^-$	-0.0017 (0.0358)	$\Delta ln(cvrr)^-$	0.0313** (0.0143)
		D_nfsm	0.0998*** (0.0292)			D_nfsm	0.0466* (0.0282)
		$\_cons$	1.0026*** (0.1748)			$\_cons$	1.0073*** (0.1888)
No. of observations = 1305 / No. of cross sections = 29				No. of observations = 1305 / No. of cross sections = 29			
Log Likelihood = 336.7621				Log Likelihood = 312.2471			

*** p < 0.01, ** p < 0.05, * p < 0.1 (Figures in parentheses are standard errors).

[b] No. of yrs, say N, for 94.5% plus adjustment = 8 [obtained from the relationship: $(1 - |\text{Coeff}|)^N < 0.055$].

[d] No. of yrs, say N, for adjustment to within 5% of complete adjustment = 9 [obtained from the relationship: $(1 - |\text{Coeff}|)^N < 0.05$].

Source: Authors

test rejects the null hypothesis of long-run symmetry (see Table 5), implying the response to price to be asymmetric, in contrast to the relevant ARDL finding. However, the response under this model to rainfall proves symmetric, with an average elasticity estimate of nearly 0.36.

Under model II, the Wald test confirms symmetry for the price elasticity estimates of 0.38 and 0.37, but asymmetry for the response to rainfall where a unit positive change increases acreage by 0.31%, but a unit negative change decreases it by 0.22 per cent. Again, this contradicts the corresponding ARDL estimation result.

TABLE 5: REACTION AND IMPACT ASYMMETRIES IN AREA RESPONSE

Variable	Model I					Model II				
	Coefficient		Wald test[h]		Response[b]	Coefficient		WALD test[h]		Response[d]
	p-value	Sign	$\chi 2$	p-value		p-value	Sign	$\chi 2$	p-value	
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
$\boldsymbol{ln}(\boldsymbol{rfhp})^{+}$	***	+	3.16	0.0756*	Asymmetric	***	+	0.00	0.9519	Symmetric
$\boldsymbol{ln}(\boldsymbol{rfhp})^{-}$	***	+				***	+			
$\boldsymbol{ln}(\boldsymbol{r\_ps})^{+}$	***	+	1.03	0.3099	Symmetric	***	+	4.24	0.0395**	Asymmetric
$\boldsymbol{ln}(\boldsymbol{r\_ps})^{-}$	***	+				**	+			
$\boldsymbol{ln}(\boldsymbol{cvrr})^{+}$	**	–	N/A		Asymmetric	NS	–	N/A		NS
$\boldsymbol{ln}(\boldsymbol{cvrr})^{-}$	NS	+				NS	–			
$\Delta\, \boldsymbol{ln}(\boldsymbol{rfhp})^{+}$	NS	–	N/A		NS	NS	–	N/A		Asymmetric
$\Delta\, \boldsymbol{ln}(\boldsymbol{rfhp})^{-}$	NS	–				**	–			
$\Delta \boldsymbol{ln}(\boldsymbol{r\_ps})^{+}$	NS	+	N/A		NS	**	+	N/A		Asymmetric
$\Delta \boldsymbol{ln}(\boldsymbol{r\_ps})^{-}$	NS	–				NS	–			
$\Delta\, \boldsymbol{ln}(\boldsymbol{cvrr})^{+}$	**	+	N/A		Asymmetric	*	+	0.14	0.7109	Symmetric
$\Delta\, \boldsymbol{ln}(\boldsymbol{cvrr})^{-}$	NS	+				**	+			

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[h] H_0: `var'_pos = `var'_neg; [b] No. of asymmetric responses (LR/SR) ≡ 75%; [d] No. of asymmetric responses (LR/SR) ≡ 60%.

*** p < 0.01, ** p < 0.05, * p < 0.1; NS → Not significant; N/A → Not applicable.

Source: Authors

The long-run responses to the undecomposed infrastructure and technology variables in their respective models, each being positive and highly significant, correspond with their ARDL counterparts but with higher and lesser elasticity estimates of 0.23 and 0.13, respectively. As for the response to the risk factor, only the long-run coefficient estimate of the positive component of the underlying variable in model I emerges significant, being negative. This estimate suggests that a 1% risk increase decreases acreage by about 0.09%, holding other variables constant, which indicates risk aversion. This result also contrasts with the relevant ARDL finding and confirms an asymmetric response to risk.

The averaged error correction coefficient estimates are similar to their counterparts from the ARDL estimation, reflecting an overall partial adjustment process (see Table 4, cols. 4 and 8) with an identical period of 9 years for adjustment to within 5% of complete adjustment. Regarding the short run, price exerts no influence under Model I, as against the significantly negative impact under the ARDL Model I – price volatility could be a plausible reason for farmers' indifference. The NARDL Model II, however, suggests a significantly negative effect of price decreases, unlike in the long run, which could stem from farmers' relatively fixed short-run demand for money income, as discussed in subsection 4.2. Price increases have an insignificant impact, rendering the short-run area response to price asymmetric. Similarly, Model II indicates impact asymmetry in response to precipitation, with only a significantly positive impact of its increases. Turning to risk, which yields unexpected positive impacts, Model I evinces asymmetry, with the negative component proving insignificant. All these results contrast with their respective ARDL findings. The NFSM impact under Model I is double that under Model II, equalling that under the ARDL Model I.

4.4 ARDL Analysis of Yield Response

In the long run (see Table 6), the relative farm harvest price and the infrastructure and technology variables under their respective models prove positive and highly significant, in conformity with the area response results. The results suggest that ceteris paribus, a 1% increase in the relative farm harvest price increases per hectare productivity by 0.21% under model I and 0.17% under model II, and vice versa; the infrastructure and technology variables indicate such impacts in the order of 0.08% each. Irrigation and rainfall during branching indicate highly significant positive and negative impacts under each model, with cross-model comparability.

These results imply, on average, that ceteris paribus, a one-unit irrigation change induces a change of about 0.56% in yield, whereas if rainfall during branching increases by one unit, yield decreases by about 0.1%, and vice versa, which seems to suggest that higher rainfall at this stage leads to excessive vegetative growth at the expense of the yield. The response to rainfall during pod filling proves negative but insignificant under both models. The maximum temperatures during December and January, which affect both flowering and pod filling, evoke significantly negative responses, the comparable elasticity estimates across the models averaging -0.9 and -1.79, respectively, the latter estimate signifying elastic long-run responses with more-than-proportionate impacts on yield. The adverse impact of higher maximum temperatures during these months likely has to do with flower drop and reduced pod set (Gaur et al., 2010).

TABLE 6: PMG ESTIMATES OF PANEL ARDL YIELD RESPONSE MODELS

Model I				Model II			
Variable	Coeff	Variable	Coeff	Variable	Coeff	Variable	Coeff
Long Run		Short Run		Long Run		Short Run	
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
		__ec	-0.6401***[b]			__ec	-0.6735***[b]
			(0.0388)				(0.0363)
$\boldsymbol{ln(rfhp)}$	0.2115***	$\Delta ln(rfhp)$	0.0215	$ln(rfhp)$	0.1729***	$\Delta ln(rfhp)$	-0.0405
	(0.0594)		(0.0351)		(0.0645)		(0.0318)
$\boldsymbol{ln(\%gia)}$	0.0772***	$\Delta ln(\%gia)$	0.4050***	$ln(npk\_ha)$	0.0762***	$\Delta ln(npk\_ha)$	0.1421***
	(0.0260)		(0.0563)		(0.0185)		(0.0293)
$(\boldsymbol{\%cpia})$	0.0058***	$\Delta(\%cpia)$	-0.0051**	$(\%cpia)$	0.0053***	$\Delta(\%cpia)$	-0.0032
	(0.0009)		(0.0025)		(0.0008)		(0.0031)
$(\boldsymbol{r\_br})$	-0.0009***	$\Delta(r\_br)$	0.0005***	(r_br)	-0.0011***	$\Delta(r\_br)$	0.0006***
	(0.0003)		(0.0001)		(0.0003)		(0.0001)
$(\boldsymbol{r\_pf})$	-0.0004	$\Delta(r\_pf)$	0.0006***	(r_pf)	-0.0004	$\Delta(r\_pf)$	0.0006***
	(0.0004)		(0.0002)		(0.0004)		(0.0002)
$\boldsymbol{ln(t\_dec)}$	-0.9421**	$\Delta ln(t\_dec)$	0.4239***	$ln(t\_dec)$	-0.8551**	$\Delta ln(t\_dec)$	0.5464***
	(0.3690)		(0.1598)		(0.3522)		(0.1604)
$\boldsymbol{ln(t\_jan)}$	-1.7334***	$\Delta ln(t\_jan)$	0.2984***	$ln(t\_jan)$	-1.8485***	$\Delta ln(t\_jan)$	0.3420***
	(0.2817)		(0.0900		(0.2655)		(0.1006)
		D_nfsm	0.0217			D_nfsm	0.0255
			(0.0277)				(0.0282)
		$\_cons$	8.9715***			$\_cons$	9.6144***
			(0.5468)				(0.5210)
No. of observations = 1305 / No. of cross sections = 29				No. of observations = 1305 / No. of cross sections = 29			
Log Likelihood = 327.336				Log Likelihood = 307.8477			

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$ (Figures in parentheses are standard errors).[b] No. of yrs, say N, for adjustment to within 5% of complete adjustment = 3 [obtained from the relationship: $(1 - |\text{Coeff}|)^N < 0.05$].

Under both models, the averaged error correction coefficient estimates bear the expected negative sign and prove highly significant, with values within the a priori expected range (see Table 6, cols. 4 and 8), each implying just three years for 95% plus adjustment. The short-run dynamics indicate that chickpea yields do not respond significantly to price changes. Infrastructure (Model I) and technology (Model II) evoke responses stronger than their long-run counterparts. Irrigation exerts a significantly negative impact under Model I. This counterintuitive result is attributable to the fact that more than two irrigations, one each at branching and pod filling, can lead to a trade-off between vegetative growth and yield – excessive irrigation enhances the former, thereby depressing the latter (Gaur et al., 2010, p.11; GoI, 2017). Rainfall and temperature variables all prove significantly positive. Their contradictory findings regarding the sign and absolute magnitude between the short and long runs indicate that the long-run response is not usually immediate. The NFSM dummy emerges positive but insignificant.

4.5 *NARDL Analysis of Yield Response*

The long-run parameter estimates in Table 7 reveal that the relative farm harvest price, rainfall during branching, and infrastructure and technology variables have insignificant impacts.

TABLE 7 : PMG ESTIMATES OF PANEL NARDL YIELD RESPONSE MODELS

Model I				Model II			
Variable	Coeff	Variable	Coeff	Variable	Coeff	Variable	Coeff
Long Run		Short Run		Long Run		Short Run	
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
		$\_\_ec$	-0.7207***[b] (0.0400)			$\_\_ec$	-0.7451***[b] (0.0392)
$\boldsymbol{ln(rfhp)^+}$	-0.0748 (0.0651)	$\Delta ln(rfhp)^+$	0.1234* (0.0669)	$ln(rfhp)^+$	-0.0662 (0.0657)	$\Delta ln(rfhp)^+$	0.0380 (0.0770)
$\boldsymbol{ln(rfhp)^-}$	0.0367 (0.0793)	$\Delta ln(rfhp)^-$	0.1111 (0.0703)	$ln(rfhp)^-$	0.0202 (0.0776)	$\Delta ln(rfhp)^-$	0.0753 (0.0582)
$\boldsymbol{ln(\%gia)}$	0.0323 (0.0304)	$\Delta ln(\%gia)$	0.4143*** (0.0671)	$ln(npk\_ha)$	0.0218 (0.0236)	$\Delta ln(npk\_ha)$	0.1599*** (0.0333)
$\boldsymbol{(\%cpia)}$	0.0035*** (0.0009)	$\Delta(\%cpia)$	0.0009* (0.0054)	$(\%cpia)$	0.0031*** (0.0008)	$\Delta(\%cpia)$	0.0015 (0.0049)
$\boldsymbol{(r\_br)^+}$	0.0001 (0.0004)	$\Delta(r\_br)^+$	0.0001 (0.0002)	$(r\_br)^+$	-0.0000 (0.0004)	$\Delta(r\_br)^+$	0.0002 (0.0002)
$\boldsymbol{(r\_br)^-}$	-0.0003 (0.0004)	$\Delta(r\_br)^-$	0.0007*** (0.0001)	$(r\_br)^-$	-0.0005 (0.0004)	$\Delta(r\_br)^-$	0.0007*** (0.0001)
$\boldsymbol{(r\_pf)^+}$	0.0008 (0.0005)	$\Delta(r\_pf)^+$	-0.0004 (0.0005)	$(r\_pf)^+$	0.0007 (0.0005)	$\Delta(r\_pf)^+$	-0.0002 (0.0005)
$\boldsymbol{(r\_pf)^-}$	0.0011** (0.0005)	$\Delta(r\_pf)^-$	0.0003 (0.0005)	$(r\_pf)^-$	0.0009* (0.0005)	$\Delta(r\_pf)^-$	0.0004 (0.0005)
$\boldsymbol{ln(t\_dec)^+}$	-1.5289*** (0.3907)	$\Delta ln(t\_dec)^+$	0.4009** (0.2038)	$ln(t\_dec)^+$	-1.5072*** (0.3828)	$\Delta ln(t\_dec)^+$	0.3243 (0.2076)
$\boldsymbol{ln(t\_dec)^-}$	-1.4313*** (0.4361)	$\Delta ln(t\_dec)^-$	0.9175*** (0.3004)	$ln(t\_dec)^-$	-1.4289*** (0.4265)	$\Delta ln(t\_dec)^-$	1.2885*** (0.2876)
$\boldsymbol{ln(t\_jan)^+}$	-1.2889*** (0.3468)	$\Delta ln(t\_jan)^+$	0.5044** (0.1966)	$ln(t\_jan)^+$	-1.5925*** (0.3407)	$\Delta ln(t\_jan)^+$	0.6920*** (0.1936)
$\boldsymbol{ln(t\_jan)^-}$	-1.9375*** (0.3251)	$\Delta ln(t\_jan)^-$	0.3453* (0.1876)	$ln(t\_jan)^-$	-2.1629*** (0.3200)	$\Delta ln(t\_jan)^-$	0.3312* (0.1934)
		D_nfsm	-0.0628* (0.0342)			D_nfsm	-0.0710** (0.0348)
		$\_cons$	4.4651*** (0.2522)			$\_cons$	4.6486*** (0.2457)
No. of observations = 1305 / No. of cross sections = 29				No. of observations = 1305 / No. of cross sections = 29			
Log Likelihood = 473.1778				Log Likelihood = 447.4234			

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$ (Figures in parentheses are standard errors).

[b] No. of yrs, say N, for adjustment to within 5% of complete adjustment = 3 [obtained from the relationship: $(1 - |\text{Coeff}|)^N < 0.05$].

The positive component of rainfall during pod-filling is also insignificant, but the negative component proves significantly positive under both models, suggesting reaction asymmetry. All of these findings contrast markedly with the relevant ARDL estimates. The insensitivity of yield to price may be attributed to its primary dependence on non-price factors With respect to infrastructure and technology, one possibility is acreage expansion into inferior-quality land, resulting in lower yield even with proportionate expansions at the extensive and intensive margins (Feng & Babcock, 2010; Miao et al., 2016). Both models imply that, all else equal, a one-unit decrease in rainfall during pod filling decreases yield by about 0.1%. Like its ARDL analogue, the long-run yield response to irrigation is significantly positive, consistent with expectations, and similar under both models but less pronounced. On average, yield changes by about 0.33% in response to a one-unit change in irrigation, ceteris paribus.

TABLE 8: REACTION AND IMPACT ASYMMETRIES IN YIELD RESPONSE

Variable	**Model I**					**Model II**				
	Coefficient		Wald test[h]		Response[b]	Coefficient		WALD Test[h]		**Response**[d]
	p-value	Sign	$\chi2$	p-value		p-value	Sign	$\chi2$	p-value	
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
$ln(rfhp)^+$	NS	−		N/A	NS	NS	−		N/A	NS
$ln(rfhp)^-$	NS	+				NS	+			
$(r\_br)^+$	NS	+		N/A	NS	NS	−		N/A	NS
$(r\_br)^-$	NS	−				NS	−			
$(r\_pf)^+$	NS	+		N/A	Asymmetric	NS	+		N/A	
$(r\_pf)^-$	**	+				*	+			Asymmetric
$ln(t\_dec)^+$	***	−	0.37	0.5420	Symmetric	***	−	0.27	0.6067	Symmetric
$ln(t\_dec)^-$	***	−				***	−			
$ln(t\_jan)^+$	***	−	15.70	0.0001***	Asymmetric	***	−	12.61	0.0004***	Asymmetric
$ln(t\_jan)^-$	***	−				***	−			
$\Delta ln(rfhp)^+$	*	+		N/A	Asymmetric	NS	+		N/A	NS
$\Delta ln(rfhp)^-$	NS	+				NS	+			
$\Delta(r\_br)^+$	NS	+		N/A	Asymmetric	NS	+		N/A	Asymmetric
$\Delta(r\_br)^-$	***	+				***	+			
$\Delta(r\_pf)^+$	NS	−		N/A	NS	NS	−		N/A	NS
$\Delta(r\_pf)^-$	NS	+				NS	+			
$\Delta ln(t\_dec$	**	+	1.49	0.2224	Symmetric	NS	+		N/A	Asymmetric
$\Delta ln(t\_dec$	***	+				***	+			
$\Delta ln(t\_jan$	**	+	0.21	0.6467	Symmetric	***	+	1.14	0.2866	Symmetric
$\Delta ln(t\_jan$	*	+				*	+			

[h] H_0: \`var'\_pos = \`var'_neg; [b] No. of asymmetric responses (LR/SR) ≡ 57%; [d] No. of asymmetric responses (LR/SR) ≡ 67%.

*** p < 0.01, ** p < 0.05, * p < 0.1; NS → Not significant; N/A → Not applicable. Source : Authors

The responses to December and January maximum temperatures are significantly negative and elastic across the models. On average, all else equal, a 1% increase in December temperature decreases yield by about 1.52% while a 1% negative change induces an increase of about 1.43%, the corresponding figures for January temperature being 1.44% and 2.05%, respectively. The responses for December temperature are much more substantial than their ARDL analogues, whereas those for January temperature are comparable. However, the Wald test results in Table 8 indicate these responses to be symmetric and asymmetric, respectively.

Table 7 (cols. 4 and 8) also reports that the averaged estimates of the error correction coefficient have nearly the same value under both models and reflect a partial adjustment process overall, akin to their ARDL counterparts but greater in absolute magnitude. However, they suggest the same three-year duration for adjustment to be within 5% of the complete adjustment. In the short run, the impacts of the positive and negative components of the relative farm harvest price are positive under both models, but only that of price increases under model I is statistically significant. This response, which is at variance with the long-run results, like the responses concerning infrastructure, technology and rainfall variables, signifies impact asymmetry for price. These findings, like those on irrigation, rainfall during pod filling, and December maximum temperature, contrast with the ARDL results. The insignificant positive component estimate of the rainfall during branching under each model renders the response to this variable asymmetric.

All the coefficient estimates of the maximum temperatures during December and January, except for the positive component estimate for December temperature under model II, are positive and statistically significant. Thus, the short-run response to the December maximum temperature is asymmetric. The response to the negative component of December maximum temperature is substantial and elastic under model II. The short-run responses to the temperature variables switch their signs over the long run. The direction of asymmetry, too, switches between the short and long runs – an important and relatively common finding in the growing NARDL literature (Shin et al., 2013). The NFSM dummy indicates significantly negative impacts under both models, in contrast to positive but insignificant ARDL estimates. The negative estimates suggest that, on average, chickpea yield decreases by about 7% with post-2010 government intervention over NFSM, possibly reflecting yield fluctuations owing to acreage expansion onto lower-grade land (as hypothesized above for the insensitivity to infrastructure and technology).

V

CONCLUSIONS

This study evaluates the area and yield responses to price and selected non-price variables using the panel data extensions of Shin et al.'s (2014) NARDL model and also provides estimates from the ARDL model of Pesaran and Shin (1998, as cited in Shin et al., 2013) and Pesaran et al. (2001). As regards the NARDL analyses, the area response results for the long run indicate asymmetric responses for the relative FHP (Model I), the risk factor (Model I) and the pre-sowing rainfall (Model II). The short-run results show asymmetry for the risk factor (Model I), relative FHP (Model II) and pre-sowing rainfall (Model II). The yield response results reveal reaction asymmetry for the rainfall during pod filling and the maximum temperature during January (both models) and impact asymmetry for the relative FHP (Model I), the rainfall during branching (both models) and the maximum temperature during December (Model II).

Thus, 67% and 33% of the variables (decomposed) under the area response Models I and II, respectively, evoke asymmetric responses in the long run, whereas the reverse holds for the short run. Similarly, chickpea yield responds asymmetrically to 40% of the variables (decomposed) under each yield response model, both in the long and short runs. The percentages of asymmetric responses under the area response Models I and II work out at 75% and 60%, respectively, with the corresponding figures for the yield response models being 57% and 67%. These findings offer fresh perspectives on pulse supply responsiveness, which could significantly inform policymaking in this domain.

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