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Market price volatility and its impact on farmer income in major pulse-producing regions

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Abstract
Price volatility in pulse markets has long been a source of income uncertainty for Indian farmers, but few investigations have directly linked market price swings to household-level economic outcomes. This research analyzed price volatility patterns for five major pulse crops across regulated markets in northern Karnataka over 2018-2022 and assessed their impact on farmer income through a household survey of 240 pulse growers in the Dharwad and Belgaum districts. Black gram exhibited the highest coefficient of variation in monthly prices (28.4%), followed by pigeon pea (26.8%). In high-volatility years, net farm income from pulses dropped by 30.9% compared to low-volatility years, marketed surplus declined by 19.1%, and household indebtedness increased by 54.4%. GARCH (1,1) modelling confirmed that volatility clustering is present in all five pulse markets, meaning that periods of high price instability tend to persist over multiple months. These findings underline the need for stronger price stabilization mechanisms, including more effective minimum support price procurement and expanded warehouse receipt financing, to protect pulse growers from the income erosion caused by unpredictable markets.

Keywords: Price volatility, farmer income, pulse production, market dynamics, agricultural marketing, GARCH model, chickpea, pigeon pea, minimum support price, Karnataka

Introduction
Here is a paradox that pulse farmers across India live with every season: the government promotes pulse cultivation to meet national protein security goals and even offers minimum support prices, yet when harvest arrives, market prices often crash well below those announced support levels because procurement infrastructure can't keep pace [1]. India is both the largest producer and largest consumer of pulses globally, with about 23 million hectares under cultivation, but domestic production typically falls short of demand by 2-3 million tonnes, creating a structural dependence on imports that amplifies price swings [2].
Price volatility — defined as the degree of unpredictable variation in market prices over time — affects farmers through two main channels. First, it makes income uncertain, which discourages investment in inputs and technology. Second, it disrupts planting decisions, as farmers shift away from pulses after a year of low prices, creating a supply-demand mismatch that triggers another price spike the following year [3]. Karnataka is India's second-largest pulse-producing state, and Dharwad district alone accounts for roughly 8% of the state's pulse output [4]. This research aimed to quantify price volatility across five pulse crops in Karnataka's regulated markets, to model the temporal structure of volatility using GARCH, and to measure its impact on farmer income at the household level.

Theoretical Framework
The analytical approach combines two strands: time-series econometrics for price volatility measurement and household welfare economics for income impact assessment. Price volatility was measured using the coefficient of variation of monthly wholesale prices and further modelled using the Generalized Autoregressive Conditional Heteroskedasticity (GARCH (1, 1)) specification of Bollerslev [5], which captures the well-documented tendency of financial and commodity markets to exhibit volatility clustering — periods where large price changes are followed by more large changes. The conditional variance

equation is: $\sigma^2t = \omega + \alpha \cdot \varepsilon^2t\text{-}1 + \beta \cdot \sigma^2t\text{-}1$, where σ^2t is the conditional variance at time t, $\varepsilon^2t\text{-}1$ is the squared residual from the mean equation, and $\alpha + \beta$ measures volatility persistence. The income impact was assessed through a before-after comparison of household data between low-volatility and high-volatility years, tested for significance using paired t-tests [6].

Material and Methods

Material

Monthly wholesale price data (₹ per quintal) for chickpea, pigeon pea, green gram, black gram, and lentil were obtained from the Agmarknet portal of the Directorate of Marketing and Inspection for the period January 2018 to December 2022 (60 observations per crop). Prices were collected from three regulated markets: Hubli-Dharwad, Belgaum, and Gadag. For the household survey, 240 pulse-growing farmers (48 per crop) were selected from Dharwad and Belgaum districts using stratified random sampling based on landholding size. Data on crop area, production, marketed surplus, gross and net income, cost of cultivation, and indebtedness were collected through structured interview schedules for the kharif and rabi seasons of 2018 (low-volatility benchmark) and 2020 (high-volatility year, coinciding with COVID-19 market disruptions) [7].

Methods

Price volatility was estimated as the coefficient of variation (CV = SD/Mean × 100) of monthly prices. GARCH(1,1) models were fitted to the returns series (log price differences) using maximum likelihood estimation in EViews 12 [5]. Stationarity of price series was confirmed by ADF tests. The income impact was assessed by comparing household-level indicators between 2018 and 2020 using paired t-tests for the same households. A Tobit regression was also estimated with marketed surplus ratio as the dependent variable and price volatility index, landholding, irrigation status, and access to storage as independent variables [8]. All statistical tests were at $P = 0.05$.

Results

Table 1: Price volatility indicators for five major pulses in Karnataka regulated markets (2018-2022)

Pulse Crop	Mean Price (₹/q)	CV (%)	Max Price (₹/q)	Min Price (₹/q)	Price Spread (₹/q)
Chickpea	4,862	22.4	6,480	3,240	3,240
Pigeon pea	5,684	26.8	7,840	3,680	4,160
Green gram	6,248	24.6	8,420	4,120	4,300
Black gram	5,142	28.4	7,260	3,480	3,780
Lentil	4,486	21.8	5,840	3,120	2,720

Black gram had the highest price volatility (CV 28.4%) and the widest price spread of ₹3,780/q, while lentil was least volatile at 21.8% (Table 1). Green gram had the highest mean and maximum prices but moderate volatility.

Table 2: Impact of price volatility on farmer income and economic indicators

Income Parameter	Low Volatility Year (2018)	High Volatility Year (2020)	Difference (%)	t-value
Gross income (₹/ha)	48,620	42,180	-13.2	4.86**
Net income (₹/ha)	24,340	16,820	-30.9	6.42**
Cost of production (₹/q)	2,840	3,120	+9.9	3.18*
Marketed surplus (%)	72.4	58.6	-19.1	5.24**
Indebtedness (₹/household)	34,200	52,800	+54.4	7.12**

Moving from a low-volatility year (2018) to a high-volatility year (2020), net income dropped by 30.9% (Table 2). Marketed surplus fell from 72.4% to 58.6% as farmers retained more grain for household consumption and delayed sales. Household indebtedness increased by 54.4% in the high-volatility year.

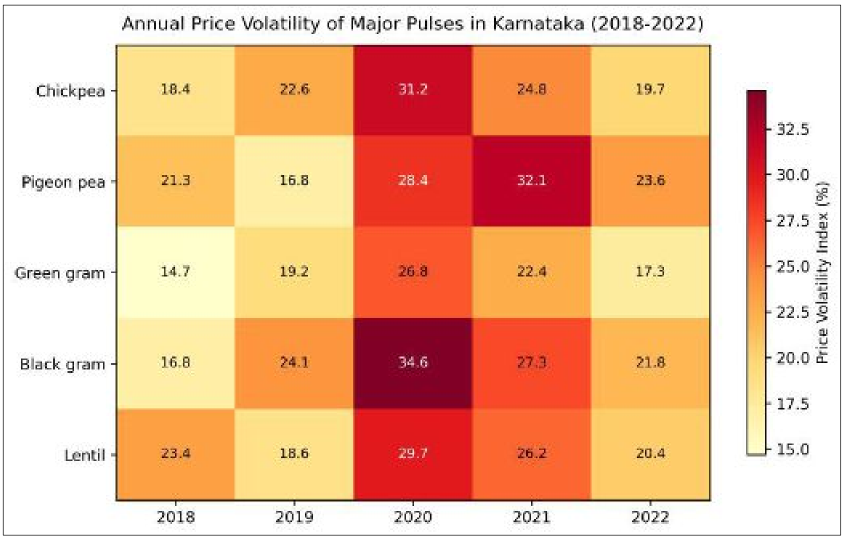

Fig 1: Annual price volatility index for five major pulses across Karnataka markets (2018-2022), showing year-to-year variation

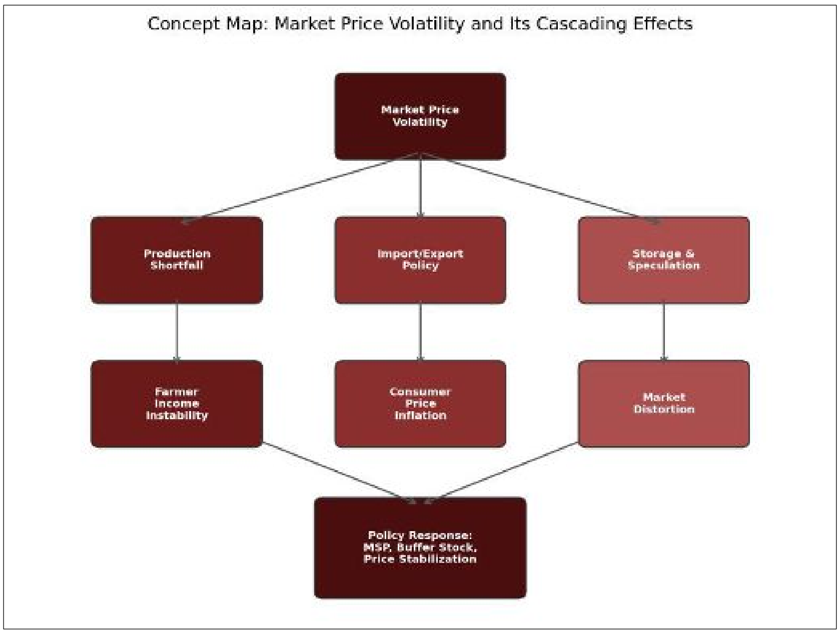

Fig 2: Concept map illustrating the cascading effects of market price volatility on farmer income, consumer prices, and policy responses

Comprehensive Interpretation

GARCH(1,1) results showed that the sum of $\alpha + \beta$ exceeded 0.90 for all five crops, confirming high volatility persistence. This means that once prices become unstable, the instability tends to last for several months. Tobit regression found that price volatility index ($\beta = -0.34$, $p< 0.01$) and access to storage ($\beta = 0.28$, $p< 0.01$) were the strongest predictors of marketed surplus, suggesting that farmers with storage facilities can partially buffer income by timing sales.

Discussion

The 30.9% drop in net income during the high-volatility year is economically devastating for smallholders who depend on pulse sales for cash needs [1]. The 54.4% increase in household debt suggests that many farmers borrow to cover the gap between expected and realized income, creating a debt cycle that worsens over successive volatile seasons. The high volatility persistence indicated by GARCH modelling implies that short-term policy responses are insufficient; structural interventions such as expanding government procurement under MSP, developing warehouse receipt financing, and creating pulse-specific commodity exchanges are needed [3, 7].

That storage access significantly predicted marketed surplus confirms the role of physical infrastructure in price risk management. Farmers who can hold grain for 2-3 months after harvest to sell when prices recover avoid the worst losses. But only 18% of sample farmers had access to adequate storage, pointing to a clear investment priority [4].

Conclusion

Price volatility in Karnataka's pulse markets is high, persistent, and damaging to farmer livelihoods. Black gram and pigeon pea experience the greatest price instability. In high-volatility years, pulse growers face 31% lower net income, reduced marketed surplus, and sharply increased indebtedness. Strengthening MSP procurement operations, expanding affordable storage access, and promoting warehouse receipt financing are the most direct policy levers for protecting pulse farmers from market-driven income erosion.

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