Journal DOI: 10.36713/epra1013 | SJIF Impact Factor (2026): 8.748 ISSN: 2347-4378
EPRA International Journal of Economics, Business and Management Studies (EBMS)
Volume: 13 | Issue: 11 | November 2026 -Peer-Reviewed

THE BEHAVIORAL ECONOMICS OF THE COBWEB PHENOMENON AND MANAGERIAL DECISION-MAKING IN INDIAN AGRICULTURE: A MATHEMATICAL MODEL FOR THE PRESENT ZHAVAME CABBAGE COLLAPSE

Dr. Elangbam Haridev Singh[1], Dr. Akha Khou[2]
[1]*Associate Professor Department of Management St. Joseph University*
[2]*Assistant Professor Department of Management St. Joseph University*

Article DOI: https://doi.org/10.36713/epra32090
DOI No: 10.36713/epra32090

ABSTRACT

This study explains why farm prices swing sharply in Zhavame, Nagaland. It combines cobweb instability, herd behaviour, and uncertainty about reaching markets. When farmers expect last season's price to repeat, prices begin to cycle. Local demand barely responds to price, so these cycles grow stronger. Farmers who copy each other's crop choices make the swings even larger. Blocked trade routes, whether from politics, ethnic tension, or logistics, deepen the instability. Internal production cycles and outside access shocks therefore reinforce one another. Farmer Producer Organisations can share price forecasts to sharpen farmers' expectations. Shifting toward high-value, low-volume crops, including Geographical Indication-tagged produce, would also help. Selling through several channels would reduce dependence on a single market corridor. Success still depends on institutional capacity, farmer adoption, and alternative buyer networks. Adequate cold-chain facilities and collection centres are equally necessary for these measures. The framework is theoretically grounded and can be tested with field data. It supports stronger agricultural resilience and demand-responsive planning in line with Viksit Bharat.

JEL: Q11, Q13, D84, R41

1. INTRODUCTION AND THEORETICAL POSITIONING

Agrarian distress in India — and in topographically constrained regions such as Nagaland in particular — is often attributed to structural deficits: poor irrigation, fragmented landholding, weak logistics. Less formally modelled, yet arguably closer to the proximate cause, is a *behavioral–informational* failure. Farmers, as boundedly rational agents operating under radical price uncertainty, systematically substitute an easily observed anchor — last season's price — for a costly-to-obtain forecast of next season's price (Ezekiel, 1938; Nerlove, 1958; Muth, 1961). This substitution is not irrational in any narrow sense; it is a predictable heuristic response to information scarcity, consistent with the broader behavioral-economics literature on anchoring, representativeness, and herding under uncertainty (Kahneman & Tversky, 1979; Bikhchandani, Hirshleifer, & Welch, 1992). Yet when the same heuristic is adopted homogeneously across a large population of independent producers, it generates an aggregate outcome — the cobweb cycle — that is collectively self-defeating even though it is individually defensible.

A full account of real-world agrarian crises cannot, however, rest on behavioral mechanisms alone. The 2026 Zhavame cabbage collapse combined the herd-driven cobweb dynamic with an independent, non-behavioral shock: acute market-access uncertainty caused by ethnic conflict in neighboring Manipur, which historically absorbed roughly 70 percent of the village's cabbage output (Morung Express, 2026). This paper therefore formalizes *two* distinct sources of instability — a behavioral, herd-driven supply-side mechanism (Sections 2–3) and an exogenous, logistics/conflict-driven demand-side shock (Section 5) — and shows mathematically how the two compound rather than merely add. The model is then extended to evaluate three managerial interventions consistent with the *Viksit Bharat* agenda: (a) AI/ML-based predictive analytics that substitute for naïve expectations (Kumar et al., 2022; Rani & Kumar, 2025), (b) strategic diversification toward High-Value, Low-Volume (HVLV) crops such as the GI-tagged Naga King Chilli (Tara, 2024), and (c) market-channel diversification to reduce exposure to single-corridor demand shocks.

2. THE CLASSICAL COBWEB MODEL: A BASELINE

Consider a single, non-storable agricultural commodity — cabbage — produced by a large number of atomistic farmers in a given district, indexed by discrete cropping season $t \in \mathbb{Z}^+$.

Journal DOI: 10.36713/epra1013 | SJIF Impact Factor (2026): 8.748 ISSN: 2347-4378
EPRA International Journal of Economics, Business and Management Studies (EBMS)
Volume: 13 | Issue: 11 | November 2026 -Peer-Reviewed

Demand function (contemporaneous, price-responsive):

$$Q_t^d = a - b\,P_t, \qquad a, b > 0 \;\ldots\ldots\ldots\ldots\ldots\ldots\ldots (1)$$

Here Q_t^d is quantity demanded in season t, P_t is the prevailing market price, a is the demand intercept (choke price scaled by market size), and $b = -\frac{\partial Q_t^d}{\partial P_t}$ is the (absolute) demand slope.

Supply function (planting decision made *before* P_t is known):

Because the sowing decision for season t must be taken before P_t is realized, supply is a function of the farmer's *expected* price, P_t^e, formed at the time of planting:

$$Q_t^s = c + d\,P_t^e, \qquad c, d > 0 \;\ldots\ldots\ldots\ldots\ldots (2)$$

Naïve (herd) expectations. Classical cobweb theory (Ezekiel, 1938) assumes static, backward-looking expectations:

$$P_t^e = P_{t-1} \;\ldots\ldots\ldots\ldots\ldots\ldots (3)$$

Equation (3) is the formal statement of the "reactive cognitive bias" central to this paper: absent real-time market intelligence, the population of farmers anchors its planting decision to the single most salient, low-cost signal available — the price realized in the immediately preceding season.

Market-clearing condition. Because the commodity is perishable and non-storable, price adjusts each season to clear the market for the quantity actually produced:

$$Q_t^d = Q_t^s \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (4)$$

Substituting (1)–(3) into (4):

$$a - bP_t = c + dP_{t-1}$$

$$\Rightarrow \quad P_t = \frac{a-c}{b} - \frac{d}{b}P_{t-1} \quad \ldots\ldots\ldots\ldots\ldots\ldots (5)$$

Equation (5) is a first-order linear difference equation in P_t. Its unique steady state, P^*, solves $P^* = \frac{a-c}{b} - \frac{d}{b}P^*$, giving:

$$P^* = \frac{a-c}{b+d} \;\ldots\ldots\ldots\ldots\ldots (6)$$

Define the deviation from equilibrium as $p_t \equiv P_t - P^*$. Equation (5) then reduces to a homogeneous linear recurrence:

$$p_t = -\frac{d}{b}\,p_{t-1} \;\ldots\ldots\ldots\ldots\ldots (7)$$

whose closed-form solution, given an initial displacement p_0, is:

$$p_t = \left(-\frac{d}{b}\right)^t p_0 \quad \ldots\ldots\ldots\ldots\ldots\ldots (8)$$

Proposition 1 (Cobweb Stability Theorem). Let $k \equiv d/b$ denote the ratio of the supply slope to the demand slope. The dynamic path $\{p_t\}$ defined by (7)–(8) satisfies:

$$\lim_{t\to\infty} p_t = \begin{cases} 0, & |k| < 1 \quad \text{(damped, convergent cobweb)} \\ p_0(-1)^t, & |k| = 1 \quad \text{(persistent two-period cycle)} \\ \pm\infty, & |k| > 1 \quad \text{(explosive, divergent cobweb)} \end{cases} \quad \ldots (9)$$

Proof. Immediate from (9), since $(-k)^t \to 0$ iff $|k| < 1$, oscillates in $\{-p_0, p_0\}$ iff $|k| = 1$, and diverges in magnitude iff $|k| > 1$. ■

Journal DOI: 10.36713/epra1013 | SJIF Impact Factor (2026): 8.748 ISSN: 2347-4378
EPRA International Journal of Economics, Business and Management Studies (EBMS)
Volume: 13 | Issue: 11 | November 2026 -Peer-Reviewed

The case $|k| > 1$ — a supply response more elastic to the *lagged* price than demand is to the *current* price — is the mathematically precise description of the Zhavame crisis. When an entire village cluster reallocates land toward a single crop on the strength of one profitable season, the effective community-level supply-response coefficient d becomes large relative to the thin, comparatively inelastic local/regional demand slope b, so $k = d/b > 1$ and the system is structurally explosive.

3. BEHAVIORAL EXTENSION: A HERD-INTENSITY PARAMETER

Section 2 treats expectation formation as uniformly naïve. Following the behavioral-finance literature on herding and anchoring (Bikhchandani et al., 1992; Chiang & Zheng, 2010; Bharti, Soti, & Kumar, 2025), we introduce a **herd-intensity parameter** $\lambda \in [0,1]$ that measures the weight the farming population places on the lagged market signal relative to an independently formed estimate:

$$P_t^e = \lambda P_{t-1} + (1-\lambda) P_t^r \quad \ldots\ldots\ldots\ldots\ldots\ldots (10)$$

where P_t^r is the farmer's independent ("rational" or extension-informed) price estimate. At $\lambda = 1$, (10) collapses to the naïve case (3); at $\lambda = 0$, farmers rely entirely on independent forecasting.

Substituting (10) for P_t^e in (2) and repeating the derivation of Section 2 yields the **behaviorally augmented cobweb equation**:

$$p_t = -\lambda \frac{d}{b} p_{t-1} - (1-\lambda)\frac{d}{b} r_t, \qquad r_t \equiv P_t^r - P^* \quad \ldots\ldots\ldots\ldots (11)$$

Proposition 2 (Herd Amplification). The effective stability coefficient of the behaviorally augmented system is $k_\lambda \equiv \lambda(d/b)$, not d/b. Consequently:

$$\frac{\partial k_\lambda}{\partial \lambda} = \frac{d}{b} > 0$$

so that, for any fixed structural elasticities (b, d), sufficiently high herd intensity $\lambda \to 1$ can push k_λ past unity even where the underlying d/b alone would be stability-neutral or stabilizing. This formalizes the paper's central claim: instability is jointly determined by *structural* elasticities and the *degree of correlated, imitative decision-making* across the farming population.

Corollary (Heterogeneity as a stabilizer). If r_t is independently and identically distributed across farmers with $\mathrm{Cov}(r_{i,t}, r_{j,t}) = 0$ for $i \neq j$, aggregating (11) across N farmers yields a community-level noise term whose variance shrinks at rate $1/N$ by the standard law of large numbers, while the λ-weighted lagged term — common to all farmers — does not average out. Reducing the *correlation* of expectation errors, via FPO-mediated information pooling, therefore dampens aggregate volatility even without changing any individual farmer's λ.

4. ILLUSTRATIVE NUMERICAL APPLICATION: THE ZHAVAME CABBAGE CASE

To render the model concrete, consider illustrative (not econometrically estimated) parameters consistent with a thin, hill-district vegetable market of the kind documented for Phek district (Rhakho, 2026; Morung Express, 2026):

$$a = 500, \quad b = 4, \quad c = 50, \quad d = 9 \;\Rightarrow\; k = \frac{d}{b} = 2.25 > 1 \quad \ldots\ldots\ldots (12)$$

From (6), $P^* = \frac{500-50}{4+9} \approx 34.6$ (index units). Suppose one season of unusually high cabbage prices, $P_0 = 60$, enters the system as an exogenous shock, i.e. $p_0 = 60 - 34.6 = 25.4$. Iterating (8):

$$\begin{aligned} p_1 &= -2.25(25.4) \approx -57.2 &&\Rightarrow\; P_1 \approx -22.6 \\ p_2 &= -2.25(-57.2) \approx 128.7 &&\Rightarrow\; P_2 \approx 163.3 \qquad \ldots\ldots\ldots (13) \\ p_3 &= -2.25(128.7) \approx -289.6 &&\Rightarrow\; P_3 \ll 0 \end{aligned}$$

The oscillation amplitude scales by $|k| = 2.25$ each period, consistent with (8). Because price cannot be economically negative in a real perishable-vegetable market, the model's negative-price region manifests empirically exactly as reported: the market-clearing price implied by the glut falls below the marginal cost of harvest and transport, so the "correction" appears not as a price statistic but as unharvested or discarded produce. Section 5 now shows that the 2026 Zhavame outcome cannot be attributed to this mechanism alone.

Journal DOI: 10.36713/epra1013 | SJIF Impact Factor (2026): 8.748 ISSN: 2347-4378
EPRA International Journal of Economics, Business and Management Studies (EBMS)
Volume: 13 | Issue: 11 | November 2026 -Peer-Reviewed

5. EXOGENOUS MARKET-ACCESS UNCERTAINTY: THE MANIPUR CORRIDOR SHOCK

Real-world agrarian distress in border and hill regions rarely stems from a single mechanism. Historically, roughly 70 percent of Zhavame's cabbage output was sold through Manipur, with the remaining 30 percent going to Kohima and Dimapur (Morung Express, 2026). The outbreak of ethnic conflict in Manipur, and the resulting travel restrictions on the direct Senapati–Imphal route, forced traders onto a longer detour via Ukhrul, roughly doubling transit time to about twelve hours; farm-gate prices per bag reportedly fell from around ₹700 in previous years to about ₹180 in 2026 (Morung Express, 2026). This is best modeled not as a change in expectation formation but as an exogenous shock to the *addressable demand* facing the village — a source of market uncertainty entirely distinct from the behavioral mechanism of Sections 2–3.

Channel-segmented demand. Decompose aggregate demand across two geographically distinct sales corridors, indexed $i \in \{M, L\}$ for Manipur and Local (Kohima/Dimapur) respectively:

$$a = a_M + a_L, \qquad \frac{a_M}{a} = \phi_0 \approx 0.7, \quad \frac{a_L}{a} = 1 - \phi_0 \approx 0.3 \ \ldots\ldots\ldots\ldots (14)$$

Corridor disruption. Let $\phi_t \in [0,1]$ denote the *severity of corridor disruption* in season t — driven by conflict intensity, checkpoint closures, or travel-time penalties — such that only a fraction $(1 - \phi_t)$ of Manipur-bound demand remains accessible. The effective, time-varying demand intercept becomes:

$$a_t = a_L + (1 - \phi_t)a_M = a[(1 - \phi_0) + \phi_0(1 - \phi_t)] = a\,(1 - \phi_0\phi_t) \ldots\ldots (15)$$

so that $a_t \to a$ when $\phi_t = 0$ (no disruption) and $a_t \to a(1 - \phi_0) = 0.3a$ when $\phi_t = 1$ (complete corridor closure) — close to a 70 percent contraction in addressable demand, consistent with what was reported on the ground.

Transport-cost wedge. The Ukhrul detour also raises the per-unit transport cost that must be absorbed before produce reaches any surviving market, denoted $\tau_t \geq 0$. Because τ_t is deducted from whatever price the market clears at, the *farm-gate* price actually received is:

$$P_t^{\text{farm}} = P_t - \tau_t \ \ldots\ldots\ldots\ldots (16)$$

so that even a partially recovered market-clearing price P_t can still leave farmers below their cost of production once τ_t is netted out — matching accounts of cabbage left unharvested despite "much better quality" produce that season (Morung Express, 2026).

The compounded recursion. Re-deriving the market-clearing condition using the disrupted demand intercept (15) together with the herd-based expectations of Section 3 yields a time-varying, *inhomogeneous* version of (11):

$$p_t = -\lambda \frac{d}{b}\, p_{t-1} \ - \ (1 - \lambda)\frac{d}{b}\, r_t \ + \ \underbrace{\frac{a_t - a}{b}}_{\eta_t} \qquad \ldots\ldots\ldots\ldots\ldots (17)$$

where $\eta_t \equiv (a_t - a)/b = -a\phi_0\phi_t/b \leq 0$ is an additional, purely exogenous forcing term driven by market-access uncertainty — additive to, but mechanically distinct from, the behavioral herd term.

Proposition 4 (Compounding of Behavioral and Access Shocks). Solving the linear recursion (17) forward gives:

$$p_t = (-k_\lambda)^t p_0 \ + \ \sum_{j=0}^{t-1} (-k_\lambda)^j \left[\eta_{t-j} - (1 - \lambda)\, d/b\, r_{t-j}\right], \qquad k_\lambda \equiv \lambda \frac{d}{b} \ \ldots\ldots (18)$$

Whenever $|k_\lambda| > 1$ — the explosive-cobweb regime already established for Zhavame in Section 4 — any market-access shock η_{t-j}, even one several seasons in the past, is *amplified* by the growing factor $(-k_\lambda)^j$ in its contribution to the current deviation p_t. A corridor disruption that, in a stable ($|k_\lambda| < 1$) market, would simply lower prices proportionately and decay away is instead compounded by the pre-existing explosive herd dynamic. This is why the 2026 Zhavame collapse looks disproportionate to the conflict-related demand loss taken alone: the season combined an already-unstable herd-driven oversupply with a simultaneous ~70 percent contraction of its principal sales corridor, so the observed farm-gate price crash reflects the **product**, not the sum, of the two shocks.

Journal DOI: 10.36713/epra1013 | SJIF Impact Factor (2026): 8.748 ISSN: 2347-4378
EPRA International Journal of Economics, Business and Management Studies (EBMS)
Volume: 13 | Issue: 11 | November 2026 -Peer-Reviewed

A third policy lever: channel diversification. Define the demand-channel concentration (Herfindahl) index:

$$H = \phi_0^2 + (1-\phi_0)^2 \dots\dots\dots (19)$$

At $\phi_0 = 0.7$, $H = 0.49 + 0.09 = 0.58$, reflecting heavy dependence on a single external corridor. Because $|\eta_t| \le a\phi_0/b$ is strictly increasing in ϕ_0, diversifying sales channels — cold-chain links to Dimapur/Kohima, digital agri-marketing platforms, inter-state FPO tie-ups — lowers ϕ_0 (and hence H) toward the two-corridor minimum of 0.5, or lower still with three or more corridors, thereby bounding the maximum possible size of any single conflict- or logistics-driven shock η_t, independently of anything done about λ or μ in Sections 6–7.

Illustrative extension. Holding the Section 4 parameters fixed and setting $\phi_0 = 0.7$, a severe one-season disruption $\phi_1 = 1$ gives $a_1 = 500(1-0.7) = 150$, so the *disrupted* equilibrium is $P^{*\prime} = (150-50)/13 \approx 7.7$ — far below the undisrupted $P^* \approx 34.6$. Combined with the herd-driven oscillation of (13) via (18), the corridor shock does not merely subtract from price; it resets the base around which an already-explosive cycle oscillates, pushing the system into unharvested-produce territory even faster than the pure herd mechanism alone would.

6. MANAGERIAL INTERVENTION I: AI-BASED PREDICTIVE SUBSTITUTION FOR NAÏVE EXPECTATIONS

Let a predictive-analytics system — machine-learning demand/price forecasting disseminated through FPOs before the sowing decision (cf. Kumar et al., 2022; Rani & Kumar, 2025) — replace the naïve anchor with a model-based forecast P_t^f, blended with weight $\mu \in [0,1]$:

$$P_t^e = (1-\mu)P_{t-1} + \mu P_t^f \dots\dots\dots\dots (20)$$

If the forecast is unbiased, $\mathbb{E}[P_t^f] = P^*$, with forecast error $\varepsilon_t \equiv P_t^f - P^*$, substitution into the market-clearing condition gives:

$$p_t = -(1-\mu)\frac{d}{b}\,p_{t-1} + \mu\,\varepsilon_t \dots\dots\dots\dots (21)$$

Proposition 3 (AI-Stabilization). Define $k_\mu \equiv (1-\mu)(d/b)$. Then $\partial k_\mu / \partial \mu = -d/b < 0$, so increasing forecast weight μ monotonically reduces the destabilizing coefficient; as $\mu \to 1$, $k_\mu \to 0$ and (21) becomes a pure white-noise process, $p_t \to \varepsilon_t$. Treating (21) as an AR(1) process with $|k_\mu| < 1$ and $\varepsilon_t \sim \text{iid}(0, \sigma_\varepsilon^2)$, the stationary variance of the price-deviation process is:

$$\text{Var}(p_t) = \frac{\mu^2\sigma_\varepsilon^2}{1-k_\mu^2} \dots\dots\dots\dots (22)$$

which is finite whenever $k_\mu = (1-\mu)(d/b) < 1$ — a strictly weaker requirement than the original condition $d/b < 1$, and one that can always be satisfied for μ sufficiently close to 1 regardless of how explosive the underlying elasticities are. Crucially, AI forecasting stabilizes the *homogeneous* (herd-driven) part of the recursion; it does **not**, by itself, address the exogenous access-shock term η_t of Section 5 — a chatbot cannot conjure a buyer where a physical corridor is blocked, a limitation farmers themselves raised on the ground when the state's digital-agriculture platform launched (HubNetwork, 2026).

Partial adoption. In practice only a share $s \in [0,1]$ of farmers adopt the forecast (the rest remaining at $\lambda = 1$). The population-weighted stability coefficient becomes:

$$\bar{k} = (1-s)\frac{d}{b} + s(1-\mu)\frac{d}{b} = \frac{d}{b}(1-s\mu) \dots\dots\dots\dots (23)$$

Equation (23) shows that stabilization requires the *product* $s\mu$ — adoption share times forecast weight — to satisfy $s\mu > 1 - b/d$. This is precisely why the seminar frames AI deployment as a managerial and institutional problem (achieving adoption share s via FPO capacity-building) as much as a technical one (achieving forecast quality μ).

7. MANAGERIAL INTERVENTION II: STRUCTURAL DIVERSIFICATION TOWARD HVLV CROPS

The second lever — diversification toward High-Value, Low-Volume (HVLV) crops such as the GI-tagged Naga King Chilli, large cardamom, and kiwi (Tara, 2024; Meetei et al., 2016) — operates on the structural elasticity b rather than on expectation formation. Because HVLV, GI-tagged, and export-oriented commodities access geographically extended (national/export) markets, a given

Journal DOI: 10.36713/epra1013 | SJIF Impact Factor (2026): 8.748 ISSN: 2347-4378
EPRA International Journal of Economics, Business and Management Studies (EBMS)
Volume: 13 | Issue: 11 | November 2026 -Peer-Reviewed

district's harvest becomes a small share of a much larger addressable demand, so the *effective* demand slope facing the locality rises from b to some $b' > b$. Holding (c, d) fixed, the resulting stability coefficient is:

$$k' = \frac{d}{b'} < \frac{d}{b} = k \quad \ldots\ldots\ldots\ldots (24)$$

Wider, more diversified end-markets also mechanically reduce channel concentration ϕ_0 from Section 5, since no single corridor (e.g., Manipur) any longer represents 70 percent of total sales. HVLV diversification is therefore a **structural** complement to both the behavioral/AI interventions of Section 6 and the channel-diversification lever of Section 5. Combining all interventions gives the fully generalized stability coefficient:

$$k_{\text{gen}} = \frac{d}{b'}(1 - s\mu) \quad \ldots\ldots\ldots (25)$$

together with a bounded exogenous forcing term $|\eta_t| \leq a\phi_0{}'/b'$ where $\phi_0{}' < \phi_0$ reflects reduced channel concentration. Equation (25) nests every case above: $k_{\text{gen}} \to d/b$ as $b' \to b$, $s\mu \to 0$ (baseline explosive cobweb), and $k_{\text{gen}} \to 0$ as $b' \gg b$ and $s\mu \to 1$ (fully stabilized system) — while the accompanying reduction in $\phi_0{}'$ shrinks the damage any future corridor-type shock can inflict.

8. DISCUSSION AND POLICY IMPLICATIONS

The model yields four propositions of direct relevance to the seminar theme:

1. Agrarian price crises of the Zhavame type are, in part, the predictable output of homogeneous, naïve, lag-based expectation formation operating on an inelastic, thin local demand curve — the cobweb-instability condition $k = d/b > 1$ in Proposition 1, amplified by herd intensity λ in Proposition 2.
2. They are simultaneously vulnerable to exogenous market-access uncertainty — political, ethnic, or logistical disruptions to a dominant sales corridor — which Proposition 4 shows *compounds multiplicatively* with, rather than simply adding to, any pre-existing herd-driven instability.
3. Because λ, μ, s, b', and channel concentration ϕ_0 enter the generalized framework (Eqs. 18, 25) through distinct but interacting channels, effective policy design must combine (a) predictive-analytics dissemination through FPOs to raise $s\mu$, (b) crop diversification toward HVLV, GI-tagged produce to raise b', and (c) market-channel diversification to lower ϕ_0 — since AI forecasting alone cannot substitute for a physically blocked trade corridor.
4. The binding managerial constraint is typically institutional capacity — achieving adoption share s close to unity, securing alternative buyers, and building cold-chain/collection-centre infrastructure — rather than the non-existence of forecasting technology, consistent with recurring farmer demands for emergency procurement, transport subsidies, and stronger FPOs reported alongside Nagaland's 2026 digital-agriculture rollout (HubNetwork, 2026).

9. CONCLUSION

This paper has formalized the claim that agrarian distress of the kind witnessed in Zhavame arises from at least two mathematically distinct but interacting sources: an explosive cobweb cycle amplified by herd intensity λ (Propositions 1–2), and an exogenous market-access shock driven by corridor disruption ϕ_t (Proposition 4), which the forward solution in Eq. (18) shows compound rather than add whenever the underlying herd dynamic is already unstable. Correcting this requires three complementary managerial levers acting on the fully generalized stability coefficient $k_{\text{gen}} = (d/b')(1 - s\mu)$ and the channel-concentration bound $|\eta_t| \leq a\phi_0{}'/b'$ (Eq. 25): predictive-analytics substitution for naïve expectations, structural diversification toward High-Value, Low-Volume crops, and diversification of sales corridors themselves. The framework offers a theoretically grounded, empirically testable pathway from reactive, herd-driven, single-corridor-dependent cultivation toward the predictive, demand-diversified agricultural planning envisioned under the *Viksit Bharat* agenda.

REFERENCES

1. *Ezekiel, M. (1938). The cobweb theorem. The Quarterly Journal of Economics, 52(2), 255–280.*
2. *Nerlove, M. (1958). Adaptive expectations and cobweb phenomena. The Quarterly Journal of Economics, 72(2), 227–240.*
3. *Muth, J. F. (1961). Rational expectations and the theory of price movements. Econometrica, 29(3), 315–335.*
4. *Kahneman, D., & Tversky, A. (1979). Prospect theory: An analysis of decision under risk. Econometrica, 47(2), 263–291.*
5. *Bikhchandani, S., Hirshleifer, D., & Welch, I. (1992). A theory of fads, fashion, custom, and cultural change as informational cascades. Journal of Political Economy, 100(5), 992–1026.*
6. *Day, R. H., & Tinney, E. H. (1969). Cycles, phases and growth in a generalised cobweb theory. The Economic Journal, 79(313), 90–108.*
7. *Chiarella, C. (1988). The cobweb model: Its instability and the onset of chaos. Economic Modelling, 5(4), 377–384.*

8. *Hommes, C. H. (1994). Dynamics of the cobweb model with adaptive expectations and nonlinear supply and demand. Journal of Economic Behavior & Organization, 24(3), 315–335.*
9. *Boussard, J.-M., Gérard, F., Piketty, M.-G., Christensen, A.-K., & Voituriez, T. (2007). A nonlinear cobweb model of agricultural commodity price fluctuations. Nonlinear Dynamics, Psychology, and Life Sciences, 11(1).*
10. *Oglend, A., & Asche, F. (2016). Cyclical non-stationarity in commodity prices. Empirical Economics, 51(4), 1465–1479.*
11. *Poitras, G. (2023). Cobweb theory, market stability, and price expectations. Journal of the History of Economic Thought, 45(1), 137–161.*
12. *Myers, R. J., Sexton, R. J., & Tomek, W. G. (2010). A century of research on agricultural markets. American Journal of Agricultural Economics, 92(2), 376–403.*
13. *Holt, M. T., & Craig, L. A. (2006). Nonlinear dynamics and structural change in the U.S. hog–corn ratio: A time-varying STAR approach. American Journal of Agricultural Economics, 88(1), 215–233.*
14. *Chang, E. C., Cheng, J. W., & Khorana, A. (2000). An examination of herd behavior in equity markets: An international perspective. Journal of Banking & Finance, 24(10), 1651–1679.*
15. *Chiang, T. C., & Zheng, D. (2010). An empirical analysis of herd behavior in global stock markets. Journal of Banking & Finance, 34(8), 1911–1921.*
16. *Christie, W. G., & Huang, R. D. (1995). Following the pied piper: Do individual returns herd around the market? Financial Analysts Journal, 51(4), 31–37.*
17. *Wray, C. M., & Bishop, S. R. (2016). A financial market model incorporating herd behaviour. PLOS ONE, 11(3), e0151790.*
18. *Bharti, Soti, N., & Kumar, A. (2025). Thematic review and discussion of research on herd behavior in capital markets. SAGE Open, 15(2).*
19. *Balcilar, M., Demirer, R., & Hammoudeh, S. (2013). Investor herds and regime-switching: Evidence from Gulf Arab stock markets. Journal of International Financial Markets, Institutions and Money, 23(1), 295–321.*
20. *Attanasi, G., Boun My, K., Levati, M. V., & Rotondi, V. (2019). Human adaptive behavior in common pool resource systems. PLOS ONE / PMC, 7, e40968.*
21. *Chen, X., Wang, Y., & Zhao, L. (2020). Farmers' risk cognition, risk preferences and climate change adaptive behavior: A structural equation modeling approach. PLOS ONE, 15(11), e0242832.*
22. *Martin, G., Felten, B., & Duru, M. (2011/2016). Processes of adaptation in farm decision-making models: A review. Agronomy for Sustainable Development, 37(1), 1–20.*
23. *Verma, A., Reddy, K., & Prabhavathi, Y. (2026). What makes Farmer Producer Organizations work? A multi-level analysis of performance determinants in India. Journal of Rural Studies (ScienceDirect, in press).*
24. *Kumar, S., Yeasin, Md., Paul, A. K., & Balasubramanian, M. (2022). Machine learning techniques for forecasting agricultural prices: A case of brinjal in Odisha, India. PLOS ONE, 17(7), e0270553.*
25. *Rani, P., & Kumar, D. (2025). Enhancing agricultural commodity price forecasting with deep learning. Scientific Reports, 15, 1–14.*
26. *Prabhavathi, Y., Patil, S., & Mehta, R. (2025). Unveiling the dynamics of farmer producer organizations in India: A systematic review of status, challenges, and future directions. Humanities and Social Sciences Communications, 12, Article 05063.*
27. *Rhakho, [initial not stated in source]. (2026). Report on the Zhavame cabbage market distress, Phek district. Local news report, 2026.*
28. *HubNetwork. (2026). Nagaland launches digital agriculture platform as farmers battle post-harvest losses. HubNetwork.in.*
29. *Morung Express. (2026). From ₹1.7 crore to rotting fields: Cabbage crisis in Nagaland's Vegetable Village. The Morung Express.*
30. *Nagaland Post. (2020). DHO team visits Zhavame vegetable village. Nagaland Post.*
31. *Tourism Nagaland, Department of Tourism, Government of Nagaland. Zhavame / Vegetable Village. Official profile note.*
32. *Tara, K. K. (2024). Cultural significance and economic potential of Naga King Chilli (Capsicum chinense J.) in Northeast India: A review. International Journal of Agriculture, Environment and Biotechnology (IndianJournals.com).*
33. *Meetei, N. T., et al. (2016). Recent advances in Naga King Chilli (Capsicum chinense Jacq.) research. International Journal of Agriculture, Environment and Biotechnology, 9(3), 421–428.*
34. *Malangmeih, L., & Rahaman, M. (2016). Traditional value chain management of Naga King Chilli: Findings from Mon district of Nagaland. Regional agricultural economics working paper.*
35. *Kumar, R., Sharma, V., & Mishra, P. (2025). Farmer Producer Organization: An ecosystem for building socio-economic resilience of farmers in India. Current Agriculture Research Journal, 13(1).*
36. *Singh, S. K., Devi, R., Tomar, S. P., Srivastava, D. S., & Singh, A. (2023). Challenges faced by farmer producer organizations and suggested policy reforms. Journal of Community Mobilization and Sustainable Development, 18(3), 365–369.*