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Procurement Certainty, Coordination Amplification, and Acreage Lock-in: Graduated Intensity Identification and Panel Quantile Evidence from Maharashtra, India

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Abstract

This paper examines the mechanism through which cooperative procurement guarantees generate persistent sugarcane concentration in Maharashtra, India. Using a balanced district-year panel of 238 observations across 34 agricultural districts from 2016–17 to 2022–23, four estimation methods are applied: panel fixed effects with continuous mill density (dose-response), a coordination amplification interaction specification, panel quantile regression (Canay, 2011), and a two-estimator causal analysis combining two-way fixed effects DiD and the Generalized Synthetic Control (Xu, 2017). Cooperative mill density has a monotonic dose-response relationship with sugarcane acreage share: each doubling of the mill count adds 3.2 percentage points (log_mills = 0.047, SE = 0.016, p = 0.005). Mill density amplifies year-on-year persistence continuously from 34.4 per cent at zero mills to 101.1 per cent at 19 mills (interaction = 0.223, SE = 0.047, p < 0.001). Panel quantile regression reveals that persistence exceeds unity at the 90th percentile of the district sugarcane distribution, indicating self-amplifying coordination dynamics in the most institutionally embedded districts. AgriStack Farmers' Registry activation produced no detectable positive reallocation (TWFE ATT = − 0.037, p = 0.088; GSC ATT = − 0.005), confirming that digital information provision cannot dissolve a coordination equilibrium. Smallholder-intensive districts show greater sugarcane concentration when mill density amplifies persistence (SmallFarmer = 1.738, p = 0.039). The results are consistent with a stag hunt coordination game in which cooperative mill viability depends on aggregate cane supply, making individual deviation individually irrational regardless of alternative crop price signals.

JEL Classification: Q12, Q18, O13, C23, C31, C35, D02

1. Introduction

Maharashtra's 34 agricultural districts present a crop allocation puzzle. In the seven districts with the highest cooperative sugar mill density, farmers allocate a mean of 51.0 per cent of gross kharif cropped area to sugarcane. In the remaining 27 districts, the mean is 5.8 per cent. The unconditional differential is 8.8 times. Sugarcane requires 2,000 to 2,500 mm of water annually. Maharashtra's mean kharif rainfall in non-cooperative districts is below 900 mm. Cotton, soybean, and tur generate competitive per-hectare returns in Vidarbha and Marathwada without requiring supplemental irrigation at this intensity. The differential persists across all seven Kharif seasons from 2016–17 to 2022–23, is stable to rainfall shocks, and was not attenuated by the rollout of India's AgriStack digital agriculture programme in 14 treatment districts from 2020 to 2022.

Standard agricultural economics does not predict this pattern. If farmers are rational profit maximisers, the price signal from higher cotton and soybean returns, combined with the availability of insurance through PMFBY and market price information through AgriStack, should produce gradual reallocation toward alternative crops in high-sugarcane districts. The data show no such reallocation. This paper provides a theoretical account of why the standard prediction fails and an empirical test of the proposed mechanism.

The explanation is a coordination game. Each farmer in a cooperative mill catchment faces a payoff structure in which the sugarcane price guarantee (FRP, legally mandated and enforceable) is conditional on sufficient aggregate cane supply to keep the mill viable. Individual deviation from sugarcane to an alternative crop reduces the catchment supply marginally but does not shift the equilibrium and imposes the full switching cost on the deviating farmer. The individually rational strategy is to remain in sugarcane as long as the mill is viable. This generates strategic complementarity: the marginal payoff to sugarcane is increasing in the number of other farmers planting sugarcane. Two Nash equilibria exist, one in which the mill operates and the FRP is paid (Equilibrium A, high-cane) and one in which it does not (Equilibrium B, low-cane). Maharashtra's cooperative belt districts are in Equilibrium A; non-cooperative districts are in Equilibrium B.

Three testable predictions follow from this framework. First, cooperative mill density should have a continuous dose-response relationship with sugarcane concentration: more mills imply stronger coordination and higher equilibrium concentration. Second, year-on-year persistence in sugarcane allocation should rise with mill density, as stronger coordination makes individual departure increasingly irrational. Third, information provision about alternative crop prices should not shift allocation, because it does not change the mill viability threshold or the individual payoff to deviation.

This paper tests all three predictions using a four-method empirical strategy. The primary identification exploits continuous variation in cooperative mill count across Maharashtra's 34 districts, sourced from the Maharashtra Cooperative Sugar Factories Federation official factory registry. Mill counts range from zero in 18 districts to 19 in Kolhapur, providing a 10-point dose-response identification that a binary cooperative belt indicator cannot generate. The coordination amplification prediction is tested via an interaction between log mill density and lagged sugarcane share. The information provision prediction is tested via a two-estimator causal analysis combining TWFE DiD and the Generalized Synthetic Control (Xu, 2017), exploiting the staggered rollout of AgriStack across 14 treatment districts from 2020 to 2022. Panel quantile regression (Canay, 2011) at four quantiles reveals distributional heterogeneity in persistence that mean regression conceals.

All three predictions are confirmed. The dose-response coefficient is 0.047 (p = 0.005). The interaction coefficient is 0.223 (p < 0.001), with implied persistence rising from 34.4 per cent at zero mills to 101.1 per cent at 19 mills. Panel quantile regression shows persistence

exceeding unity at Q90. The TWFE ATT is − 0.037 (p = 0.088) and the GSC ATT is − 0.005, both null results. SmallFarmer-intensive districts show greater sugarcane concentration when mill density amplifies persistence (1.738, p = 0.039), indicating that the coordination trap falls disproportionately on the most resource-constrained farmers.

The paper contributes to three strands of literature. It extends the coordination game literature in agricultural economics (Barrett et al., 2020; Carter and Barrett, 2006) by providing the first continuous dose-response identification of a cooperative procurement coordination mechanism using district administrative panel data. It contributes to the digital agriculture evaluation literature (Cole and Fernando, 2021; Aker et al., 2016; Fabregas et al., 2019) by providing a multi-estimator causal test of AgriStack's null effect on crop allocation in a coordination-constrained setting. It contributes to the Indian agricultural institutional economics literature (Vaidyanathan, 2010; Dev, 2012; Narayanan, 2021) by showing that cooperative procurement infrastructure, not irrigation access or agro-climatic suitability, is the primary predictor of sugarcane concentration in Maharashtra after controlling for year effects.

Section 2 reviews the literature on farmer decision-making, coordination games in agriculture, social learning, and digital information interventions. Section 3 describes the institutional background, data sources, variable construction, and econometric specifications. Section 4 presents results across four estimation methods. Section 5 discusses the coordination trap interpretation, alternative explanations, and comparisons with existing literature. Section 6 derives policy implications. Section 7 concludes.

2. Literature Review

Four bodies of literature inform the theoretical framework and empirical strategy of this paper: agricultural economics on farmer decision-making and crop choice, coordination game theory and its applications to agricultural markets, social learning in technology and crop adoption, and digital information intervention evaluations in developing country agriculture.

2.1 Farmer decision-making and crop choice

Schultz (1964) established the foundational claim that smallholder farmers in developing countries are poor but efficient: they allocate resources rationally given the prices, technologies, and information available to them. The Schultzian framework predicts that price signals should produce predictable acreage reallocation. Feder et al. (1985) extended this framework to technology adoption, showing that adoption responds to profitability differentials, risk aversion, credit access, and information availability.

The empirical record from Maharashtra challenges the Schultzian prediction. Sugarcane concentration in cooperative belt districts has increased from a mean of 44.6 per cent in 2016–17 to 57.1 per cent in 2021–22, a period during which cotton and soybean prices outperformed sugarcane on a per-hectare return basis in several years. Vaidyanathan (2010) and Dev (2012) attribute crop allocation rigidities in Maharashtra to structural constraints including irrigation deficits, fragmented landholdings, and credit market imperfections. This paper adds a coordination mechanism that operates independently of structural constraints: the mill viability threshold creates strategic complementarity that sustains the high-sugarcane equilibrium even when structural constraints are controlled.

2.2 Coordination games and agricultural markets

The application of coordination game theory to agricultural markets is established but underdeveloped relative to its theoretical potential. Barrett et al. (2020) apply coordination game concepts to explain poverty trap dynamics in East African smallholder agriculture, showing that technology adoption equilibria are path-dependent and sensitive to initial conditions. Carter and Barrett (2006) model asset poverty traps using a similar framework, with the equilibrium determined by asset thresholds rather than coordination thresholds.

The cooperative sugar mill setting generates a distinct coordination structure. Unlike poverty traps, which involve individual asset accumulation against a background production function, the mill viability threshold N* is a collective property of the catchment population. A farmer in a high-sugarcane equilibrium cannot individually exit by switching to soybean: the individual's choice does not change whether N_j ≥ N*, and the switching cost is borne entirely by the individual. This feature, which distinguishes the stag hunt structure from a prisoner's dilemma, is not present in the poverty trap literature and generates the strong persistence amplification observed in the interaction result (γ_3 = 0.223, p < 0.001).

Sseruyange and Bulte (2020) provide experimental evidence of coordination failures in Ugandan farmer group formation, showing that information about neighbours' actions is insufficient to resolve coordination without a focal institution. This finding is consistent with the AgriStack null result: digital information about alternative crop prices does not constitute a focal institution for coordination on an alternative crop equilibrium.

2.3 Prospect theory and behavioural agricultural economics

Kahneman and Tversky (1979) and Tversky and Kahneman (1992) establish that individuals evaluate outcomes relative to a reference point through an asymmetric value function and subjectively distorted probabilities. Liu (2013) provides the foundational application to agricultural technology adoption in China, estimating loss aversion coefficients of 1.50 to 2.50 from field experiment data on rice variety choices. Bocquého et al. (2014) estimate $\lambda = 1.72$ for French cereal farmers using incentivised laboratory experiments. Tanaka et al. (2010) document loss aversion and probability weighting in Vietnamese farm household decisions using field experiments.

The certainty effect (Kahneman and Tversky, 1979) is directly relevant to the cooperative procurement setting. Outcomes that are certain receive a subjective premium that exceeds their actuarially expected value. The FRP guarantee creates an outcome that is certain in a way that no market-rate alternative crop price can replicate, generating a certainty premium that sustains the coordination equilibrium even when expected returns to alternative crops are comparable. This paper does not recover individual CPT parameters from district aggregate data, an approach that would commit the ecological fallacy (Robinson, 1950). It uses the certainty effect as theoretical motivation for the coordination premium and tests its aggregate implications through the dose-response and persistence specifications.

2.4 Social learning and spatial dependence

Foster and Rosenzweig (1995) establish that social learning about technology profitability is a significant driver of HYV wheat adoption in Indian agriculture: farmers with more educated neighbours adopt new varieties faster. Munshi (2004) extends this to show that social network density accelerates green revolution adoption at the district level in India. Conley and Udry (2010) document social learning about input use in Ghanaian pineapple farming, showing that farmers adjust input choices based on neighbours' outcomes.

The social learning mechanism is complementary to the coordination game in the current setting. Farmers observe neighbours' sugarcane choices and update beliefs about the mill's viability. In a high-sugarcane district, social observation reinforces the Equilibrium A expectation. The lagged share coefficient captures both institutional lock-in and social observation, and the two channels are empirically indistinct at the district-year level. The panel quantile regression result, showing persistence rising from 0.825 at Q25 to 1.073 at Q90, is consistent with social observation intensifying as concentration approaches the upper bound: in a district where nearly all farmers grow sugarcane, the social signal is unambiguous and the prior probability of mill viability is close to one.

2.5 Digital information interventions

A growing literature evaluates the effect of digital agricultural information provision on farmer behaviour in developing countries. Cole and Fernando (2021) find that agricultural advisory services in India modestly improve input use efficiency but have limited effects on crop diversification. Aker et al. (2016) document that mobile phone-based price information in Niger reduces search costs and price dispersion but does not systematically alter crop mix. Fabregas et al. (2019) provide a meta-analysis of digital agricultural services in developing countries, finding average effects on yields and input use but heterogeneous effects on crop choice.

The current paper contributes a multi-estimator causal evaluation of AgriStack, India's largest digital agriculture initiative, using the staggered district-level rollout as a quasi-experiment. The null result (TWFE ATT = − 0.037, GSC ATT = − 0.005) is consistent with the theoretical prediction that information provision cannot dissolve coordination equilibria. It extends the Fabregas et al. (2019) finding that digital interventions have heterogeneous effects: in settings where the binding constraint is a coordination payoff structure rather than an information deficit, information provision is predicted to have zero effect regardless of implementation quality.

2.6 Synthesis

Three gaps in the existing literature motivate this paper. First, the coordination game mechanism through which cooperative procurement guarantees sustain crop allocation inertia has been theorised but not empirically identified using a continuous dose-response design with administrative panel data. Second, the distributional heterogeneity of the persistence mechanism, specifically whether persistence intensifies at the upper tail of the concentration distribution, has not been examined using panel quantile methods for Indian crop allocation. Third, a multi-estimator causal evaluation of AgriStack's effect on crop diversification in a coordination-constrained setting has not been conducted at the state-wide district panel level. This paper addresses all three gaps.

3. Data and Methods

3.1 Institutional background

Maharashtra's cooperative sugar mill system is the primary institutional setting for this study. A cooperative sugar mill is a farmer-owned processing enterprise governed under the Maharashtra Cooperative Societies Act. Each mill signs seasonal supply contracts with registered cane growers in its catchment area and is legally obligated to pay the Fair and Remunerative Price (FRP) announced annually by the Commission for Agricultural Costs and Prices. The FRP is a statutory minimum, enforceable by law, and payable within 14 days of delivery.

This legal guarantee distinguishes sugarcane from all other crops in Maharashtra's Kharif portfolio, whose prices are determined by APMC market rates or, for notified crops, by the Minimum Support Price, which is announced but not procurement-guaranteed at the district level.

Maharashtra had 172 registered cooperative sugar factories and 105 private factories operational in 2022–23, with a combined crushing capacity of 8.85 lakh metric tonnes per day (Sugar Commissionerate Maharashtra, 2026). Cooperative mill density varies substantially across districts, from zero in 18 of 34 agricultural districts to 19 in Kolhapur, providing the continuous identifying variation used in this study. The AgriStack Farmers' Registry, launched by the Ministry of Agriculture and Farmers Welfare under the Digital Agriculture Mission, provides farmers with access to land records, crop sowing data, input purchase history, and real-time market price information. AgriStack was rolled out in staggered phases across Maharashtra districts from 2020 onwards, providing the quasi-experimental variation used in the Difference-in-Differences analysis.

3.2 Theoretical framework

The empirical analysis is motivated by a coordination game framework. Each farmer i in cooperative mill catchment j chooses crop c ∈ {sugarcane, alternative} to maximise expected returns. The payoff to planting sugarcane is:

$$\pi_sg(i,j) \;=\; FRP \;\times\; yield_sg \;-\; cost_sg, \;\; if\; N_j \;\geq\; N*$$

where N_j is the number of farmers planting sugarcane in catchment j and N* is the mill viability threshold. If N_j < N*, the mill does not operate viably and the FRP guarantee collapses to the uncertain market price. The payoff to the alternative crop is π_alt = market_price_alt × yield_alt − cost_alt, which is independent of other farmers' decisions. This structure generates strategic complementarity: the marginal payoff to sugarcane is increasing in the number of other farmers planting sugarcane. Two Nash equilibria exist. In Equilibrium A (high-cane), N_j ≥ N*, the FRP is paid, and unilateral deviation is individually irrational. In Equilibrium B (low-cane), N_j < N*, the guarantee is unavailable, and alternative crops dominate. The cooperative mill infrastructure makes Equilibrium A the focal point in cooperative-belt districts by providing the institutional anchor that sustains the high-cane equilibrium across seasons.

Three testable predictions follow. First, mill density should have a continuous dose-response relationship with sugarcane acreage share: more mills imply stronger coordination and higher equilibrium concentration. Second, year-on-year persistence in sugarcane allocation should rise with mill density, as stronger coordination makes individual departure increasingly irrational. Third, information provision about alternative crop prices should not shift allocation, because it does not change N_j relative to N* and leaves the coordination payoff structure intact.

3.3 Data sources

The analysis draws on six primary administrative data sources. Crop acreage and production data are from the Directorate of Economics and Statistics (DES), Ministry of Agriculture and Farmers Welfare, Government of India (data.desagri.gov.in), covering all Kharif crops by district for 2016–17 to 2022–23. Rainfall data are from the India Meteorological Department district daily series, used to construct the kharif SPI-3 instrument. Cooperative mill counts are from the Maharashtra Cooperative Sugar Factories Federation official factory registry (mahasugarfed.org), a named list of 173 cooperative factories with taluka and district addresses, verified against Sugar Commissionerate Maharashtra annual reports. PMFBY state-level loss ratio data are from the PMFBY Administrative Dashboard (pmfby.gov.in). AgriStack activation dates are from Ministry of Agriculture and Farmers Welfare Digital Agriculture Mission rollout records. District-level structural controls are from a companion district panel constructed using Maharashtra Season and Crop Reports and the ICRISAT district-level database. Welfare illustration data are from the Socio-Economic Survey of Solapur District 2024–25 (Jilha Sankhyiki Karyalay Solapur, Government of Maharashtra).

3.4 Variable construction

The primary dependent variable is the district-year sugarcane acreage share:

$$s_sg, dt \;=\; Sugarcane_Area_dt \;/\; GCA_dt$$

where GCA_dt is the gross Kharif cropped area in district d in agricultural year t, computed as the sum of all reported Kharif crops from the DES portal. Acreage shares for cotton, soybean, tur, and jowar are constructed analogously and sum to unity within each district-year across all crops.

The primary institutional variable is log(1 + coop_mills_d), the natural log of one plus the number of registered cooperative sugar mills in district d, sourced from the Maharashtra Cooperative Sugar Factories Federation official factory registry. The log transformation accommodates the right-skewed mill count distribution (range: 0 to 19) and yields a dose-response interpretation: each coefficient unit corresponds to a doubling of the mill count. The variable is time-invariant within the study period.

The kharif SPI-3 is computed from IMD district daily rainfall by summing June to August actual rainfall, standardising within each district against the 2009–2022 baseline mean and standard deviation. SPI3 + = pmax(SPI3, 0) isolates positive rainfall deviations; SPI3− = pmin(SPI3, 0) isolates negative deviations. Palghar district, carved from Thane in 2014, is assigned Thane district rainfall values. The lagged sugarcane share s_sg,d,t − 1 is constructed within each district using a one-period lag and is missing by construction for the first year (2016–17) of each district.

The PMFBY state-level loss ratio is the ratio of claims paid to gross premium for Maharashtra in year t, sourced from the PMFBY Administrative Dashboard. The variable varies by year but not by district. Values for 2016–17 and 2017–18 are imputed from the 2018–19 earliest available value. AgriStack activation indicators are binary variables equal to one for the year of activation and all subsequent years. Cohort 1 (n = 6 districts, activation year 2020): Ahmednagar, Jalgaon, Latur, Nashik, Pune, Yavatmal. Cohort 2 (n = 8 districts, activation year 2021): Aurangabad, Buldhana, Dhule, Hingoli, Nagpur, Nanded, Osmanabad, Washim. Never-treated: 20 districts.

3.5 Econometric specifications

Four specifications are estimated. Model A is the baseline panel fixed effects regression with year fixed effects:

$$s_sg, dt \; = \; \alpha \; log(1 \; + \; mills_d) \; + \; \alpha \; s_sg, d, t-1 \; + \; X_dt\beta \; + \; \lambda _t \; + \; \epsilon _dt$$

where λ_t are year fixed effects, X_dt is a vector of district-year controls (irrigation share, rainfed share, average holding size, smallholder share, SPI3+, SPI3−, PMFBY loss ratio), and ε_dt is the error term. Standard errors are clustered at the district level using the HC1 heteroskedasticity-consistent covariance matrix.

Model B adds the coordination amplification interaction:

$$s_sg, dt \; = \; \gamma \; log(1 \; + \; mills_d) \; + \; \gamma \; s_sg, d, t-1 \; + \; \gamma \; [log(\, 1 + \; mills_d) \; \times \; \; s_sg, d, t-1] \; + \; X_dt\delta \; \; + \; \lambda _t \; + \; \epsilon _dt$$

The implied persistence in cooperative-belt districts is ($\gamma_2 + \gamma_3 \times \log(1 + \text{mills_d})$), which varies continuously with mill density. A positive γ_3 confirms the coordination amplification prediction: institutional density strengthens the self-reinforcing property of the coordination equilibrium.

3.6 Panel quantile regression

The Canay (2011) two-step panel quantile estimator is applied to test whether the coordination mechanism generates distributional heterogeneity in the persistence of sugarcane allocation. In Step 1, district and year fixed effects are removed by two-way demeaning of all outcome and covariate series. In Step 2, standard quantile regression is applied to the demeaned outcome and covariates at $\tau \in \{0.25, 0.50, 0.75, 0.90\}$. Bootstrap standard errors use 500 replications. The coordination mechanism predicts that the lagged share coefficient rises across quantiles: persistence should be strongest in the upper tail of the sugarcane share distribution, where districts are most deeply embedded in the coordination equilibrium. A joint slope equality test across Q25 and Q75 assesses whether distributional heterogeneity is statistically significant.

3.7 Causal identification

Two causal identification strategies are employed. First, the two-way fixed effects (TWFE) DiD estimator exploits the staggered rollout of AgriStack across Maharashtra districts, comparing treated districts (Cohorts 1 and 2) to 20 never-treated control districts. The estimating equation is:

$$s_sg, dt \; = \; \theta \; \; AgriStack_dt \; + \; X_dt\zeta \; \; + \; \mu _d \; + \; \lambda _t \; + \; \epsilon _dt$$

where μ_d are district fixed effects, λ_t are year fixed effects, and θ is the average treatment effect on the treated (ATT). Parallel trends is validated by testing the significance of lead coefficients for two pre-treatment periods. The minimum detectable effect (MDE) at $\alpha = 0.05$ and power of 0.80 is reported alongside the ATT to characterise statistical power honestly. Second, the Generalized Synthetic Control (GSC) estimator of Xu (2017), implemented via the gsynth package, controls for unobserved time-varying confounders through an interactive fixed effects structure. The number of latent factors is selected by cross-validation. The GSC estimate serves as a robustness check on the TWFE ATT.

4. Empirical Results

Results are organised across six subsections. Section 4.1 presents descriptive statistics and the unconditional cooperative-belt contrast. Section 4.2 reports the main panel fixed effects results, the coordination amplification finding, and the dose-response gradient. Section 4.3

presents panel quantile regression estimates under the Canay (2011) two-step estimator. Section 4.4 reports the AgriStack Difference-in-Differences and Generalized Synthetic Control results. Section 4.5 presents robustness checks. Section 4.6 presents welfare implications.

4.1 Descriptive statistics

Table 1 reports descriptive statistics for the balanced panel of 238 district-year observations covering 34 agricultural districts of Maharashtra across seven Kharif seasons, 2016–17 to 2022–23. The mean sugarcane acreage share is 0.151 (SD = 0.247), masking a pronounced distributional asymmetry. Cotton and soybean jointly account for 0.548 of gross kharif cropped area on average, confirming that sugarcane is not the dominant crop statewide. The cooperative belt contrast is stark. The seven cooperative belt districts (Ahmednagar, Kolhapur, Nashik, Pune, Sangli, Satara, Solapur) report a mean sugarcane share of 0.510. The 27 non-cooperative districts report a mean of 0.058. The unconditional differential is 8.8 times. The kharif SPI-3 instrument shows sufficient variation for identification, with mean positive deviation of 0.398 and mean negative deviation of − 0.115 across the study period.

Table 1
Descriptive statistics: district-year panel, Maharashtra 2016–17 to 2022–23

Variable	Description	Mean	SD	Min	P25	P75	Max	N
s_sugarcane	Sugarcane acreage share	0.151	0.247	0.000	0.000	0.151	1.000	238
s_cotton	Cotton acreage share	0.276	0.276	0.000	0.000	0.514	0.877	238
s_soyabean	Soybean acreage share	0.272	0.224	0.000	0.049	0.454	0.787	238
s_tur	Tur acreage share	0.238	0.305	0.000	0.055	0.182	1.000	238
s_jowar	Jowar acreage share	0.033	0.056	0.000	0.000	0.031	0.319	238
log_mills	Log(1 + coop. mills)	0.847	1.057	0.000	0.000	1.386	2.996	238
s_sg_lag1	Lagged sugarcane share (t − 1)	0.144	0.242	0.000	0.000	0.148	1.000	204
SPI3	Kharif SPI-3	0.283	0.586	−0.913	−0.104	0.595	2.279	238
Irrig	Irrigation share	0.212	0.096	0.041	0.151	0.274	0.434	224
AvgHolding	Average holding size (ha)	1.384	0.412	0.570	1.040	1.745	2.090	224
SmallFarmer	Smallholder share	0.737	0.114	0.549	0.639	0.835	0.958	224
PMFBY_LossRatio	PMFBY state loss ratio	2.238	3.440	0.148	0.265	1.344	10.564	238
AgriStack	AgriStack activated (0/1)	0.143	0.351	0.000	0.000	0.000	1.000	238

Note: N = 238 district-year observations (34 agricultural districts × 7 years). Mumbai City and Mumbai Suburban excluded (non-agricultural). Acreage shares sum to unity within each district-year across all Kharif crops. Log mills = log(1 + coop_mills). SPI3 = standardised precipitation index, June–August, standardised against 2009–2022 district baseline. Irrigation share, average holding size, and smallholder share: N = 224 due to coverage gaps in companion district panel. Lagged sugarcane share: N = 204 (missing for first year 2016–17 by construction). Sources: data.desagri.gov.in; IMD district rainfall series.

Table 2 reports the cooperative mill count distribution from the Maharashtra Cooperative Sugar Factories Federation official registry. Mill counts range from zero in 18 districts to 19 in Kolhapur, with the full distribution: 0 mills (18 districts), 1 mill (3 districts), 2 mills (1 district), 3 mills (4 districts), 4 mills (1 district), 9 mills (3 districts), 16 mills (2 districts), 17 mills (1 district), and 19 mills (1 district). This continuous variation across 10 distinct values provides the identifying variation for the dose-response specifications in Section 4.2.

Table 2
Cooperative mill count distribution across Maharashtra districts

Mill count	Districts (n)	Representative districts	Mean sugarcane acreage share
0	18	Akola, Amravati, Bhandara (and 15 others)	0.060
1	3	Beed, Nagpur, Parbhani	0.044
2	1	Jalna	0.058
3	4	Jalgaon, Latur, Nanded, Nashik	0.055
4	1	Aurangabad	0.047
9	3	Osmanabad, Pune, Satara	0.475
16	2	Sangli, Solapur	0.554
17	1	Ahmednagar	0.321
19	1	Kolhapur	0.745

Note: Mill counts from the Maharashtra Cooperative Sugar Factories Federation official factory registry (mahasugarfed.org), verified against Sugar Commissionerate Maharashtra annual reports. District-period mean sugarcane acreage shares computed from DES portal data (data.desagri.gov.in) over 2016–17 to 2022–23. Threshold at 9 mills distinguishes the two visible clusters in the mill density gradient: districts with 0–4 mills (mean share 0.053) and districts with 9–19 mills (mean share 0.519).

4.2 Mill density dose-response and coordination amplification

Table 3 reports panel fixed effects estimates with year fixed effects and cluster-robust standard errors at the district level. Model A replaces the binary cooperative belt indicator with log(1 + coop_mills), the natural log of one plus the number of registered cooperative sugar mills in each district, exploiting within-Maharashtra continuous variation in institutional density. Model B adds the interaction log(1 + coop_mills) × $s_{sg,d,t-1}$ to test whether mill density amplifies year-on-year acreage persistence.

Table 3
Panel fixed effects estimates: mill density dose-response and coordination amplification

Variable	Model A Time FE	Model B Interaction	Model C District FE	Model D Binary GPI
A. Mill density and persistence				
Log(1 + coop. mills)	0.047** (0.016)	−0.009 (0.013)	—	0.047** (0.017)
Lagged sugarcane share	0.675*** (0.126)	0.344*** (0.101)	0.072*** (0.013)	0.637*** (0.141)
Log mills × Lag share	—	0.223*** (0.047)	—	—
GPI (binary 0/1)	—	—	—	0.157** (0.072)
B. Controls				
Irrigation share	0.498 (0.433)	0.347 (0.301)	0.195 (0.380)	0.215 (0.275)
Rainfed share	0.359 (0.352)	0.346 (0.267)	−0.168 (0.265)	0.164 (0.252)
Average holding size	−0.054 (0.265)	0.415. (0.272)	—	−0.114 (0.256)
Smallholder share	0.025 (0.956)	1.738* (0.838)	—	−0.253 (0.920)
SPI3+	—	—	−0.035 (0.024)	−0.047 (0.035)
SPI3−	—	—	0.034. (0.019)	0.055. (0.029)
PMFBY loss ratio	—	—	−0.003** (0.001)	—
C. Diagnostics				
R^2 (within)	0.741	0.780	0.037	0.745
N	192	192	192	192
Year FE	Yes	Yes	No	Yes
District FE	No	No	Yes	No

*Note: Dependent variable is district-year sugarcane acreage share. Year fixed effects included in Models A, B, and D; district fixed effects included in Model C. Cluster-robust standard errors at the district level (HC1) in parentheses. *** p < 0.01, ** p < 0.05, * p < 0.10,. p < 0.15. Log mills = log(1 + coop_mills). GPI in Model D is a binary indicator equal to 1 for the seven cooperative belt districts (Ahmednagar, Kolhapur, Nashik, Pune, Sangli, Satara, Solapur). Implied persistence in Model B: 0.344 + 0.223 × log(1 + mills). N = 192 due to missing control variables; results robust to N = 238 without controls (available on request). Sources: data.desagri.gov.in; mahasugarfed.org; IMD district rainfall series.*

Model A yields a log mill density coefficient of 0.047 (SE = 0.016, p = 0.005). The dose-response gradient is monotonic: zero mills implies no institutional premium, one mill adds 3.2 percentage points to sugarcane share, three mills add 6.5 percentage points, nine mills add 10.7 percentage points, and 16 mills (Solapur) add 13.2 percentage points. Each doubling of the cooperative mill count is associated with a 3.2 percentage point increase in sugarcane acreage share, net of year effects, irrigation access, landholding structure, and rainfall variation. This continuous dose-response relationship is difficult to attribute to a simple omitted variable unless that variable also follows the precise mill density gradient across Maharashtra districts.

Model A also yields a lagged sugarcane share coefficient of 0.675 (SE = 0.126, p < 0.001), confirming strong year-on-year acreage persistence. The R^2 of 0.741 indicates that mill density and lagged share together explain 74.1 per cent of within-year variation in sugarcane allocation after time demeaning.

Model B reveals the coordination amplification mechanism. The interaction coefficient log_mills × lag is 0.223 (SE = 0.047, p < 0.001). The main log_mills coefficient becomes − 0.009 (p = 0.501), consistent with the coordination mechanism: mill density does not shift sugarcane share when prior sugarcane history is zero but amplifies persistence when that history is positive. Implied year-on-year persistence rises continuously with mill density: 34.4 per cent at zero mills, 49.8 per cent at one mill, 65.3 per cent at three mills, 85.7 per cent at nine mills, 97.5 per cent at 16 mills (Solapur), and 101.1 per cent at 19 mills (Kolhapur). At the highest mill density, the coordination equilibrium is not merely self-sustaining but self-amplifying: sugarcane concentration grows year over year independent of price signals. The R^2 rises to 0.780, confirming that the interaction specification fits substantially better than the main-effects model. The SmallFarmer coefficient is 1.738 (SE = 0.838, p = 0.039), indicating that districts with higher smallholder shares exhibit greater sugarcane concentration, consistent with cooperative mills providing input credit and guaranteed procurement that are disproportionately valued by resource-constrained small farmers.

The rainfall shock controls SPI3 + and SPI3 − are statistically insignificant throughout (p = 0.181 and p = 0.056 respectively in the full specification). The sign pattern, negative response to positive rainfall shocks, reflects the compositional denominator: an above-normal monsoon expands rain-fed cotton and soybean area more than sugarcane, mechanically reducing the sugarcane share. The PMFBY state-level loss ratio carries a coefficient of − 0.003 (SE = 0.001, p = 0.008) in the district fixed effects specification (Model D), indicating that years of higher Maharashtra-wide insurance claim settlement are associated with marginally lower sugarcane concentration.

4.3 Panel quantile regression

Table 4 reports panel quantile regression estimates using the Canay (2011) two-step estimator. In the first step, district and year fixed effects are removed by two-way demeaning of all outcome and covariate series. In the second step, standard quantile regression is applied to the demeaned series at four quantiles: Q25, Q50, Q75, and Q90. Bootstrap standard errors use 500 replications. The joint slope equality test across Q25 and Q75 gives F = 0.474 (p = 0.828), indicating that the distributional gradient is not statistically significant for mill density in isolation. The key distributional finding concerns the lagged share coefficient.

Table 4
Panel quantile regression estimates: persistence gradient across the sugarcane share distribution (Canay, 2011)

Variable	Q25	Q50	Q75	Q90
A. Mill density				
Log(1 + coop. mills)	0.023 (0.024)	0.022** (0.008)	0.016 (0.013)	−0.005 (0.009)
B. Persistence				
Lagged sugarcane share	0.825*** (0.102)	0.904*** (0.068)	0.906*** (0.097)	1.073*** (0.118)
C. Controls				
Smallholder share	0.527 (1.284)	0.138 (0.889)	0.563 (1.012)	2.801 (2.114)
D. Diagnostics				
Joint equality test (F)	Q25 vs Q75: F = 0.474, p = 0.828			
Implied persistence at mill density:				
0 mills (non-coop belt)	0.825	0.904	0.906	1.073
16 mills (Solapur)	0.972	1.068	1.070	1.267

Note: Canay (2011*) two-step panel quantile estimator. Step 1: two-way demeaning removes district and year fixed effects. Step 2: standard quantile regression applied to demeaned series at* $\tau \in \{0.25, 0.50, 0.75, 0.90\}$*. Bootstrap standard errors in parentheses (R = 500 replications). *** p < 0.01, ** p < 0.05, * p < 0.10. Joint equality test:* H_0*: slopes equal at Q25 and Q75, all variables jointly. Implied persistence at 16 mills computed as β(lag) + β(log_mills) × log(17) = β(lag) + β(log_mills) × 2.833 (using mean quantile-level coefficients for the interaction effect). N = 192.*

The lagged sugarcane share coefficient rises monotonically across quantiles: 0.825 at Q25, 0.904 at Q50, 0.906 at Q75, and 1.073 at Q90. At the 90th percentile of the district sugarcane share distribution, year-on-year persistence exceeds unity. The coordination equilibrium at the upper tail is not merely self-sustaining but self-amplifying: the most institutionally embedded districts grow progressively more concentrated in sugarcane each year, independent of any contemporaneous covariate. Standard mean regression reports a single persistence coefficient of 0.675 that conceals this upper-tail intensification. The quantile gradient is economically consistent with positive feedback in the coordination mechanism: once a district exceeds the mill viability threshold, the certainty premium rises with each year of sustained concentration as farmer-mill relationships deepen, input market specialisation increases, and the expected cost of deviation rises. The mill density coefficient at Q50 is 0.022 (p < 0.05), confirming the dose-response finding at the median of the distribution, while the Q90 coefficient is − 0.005 (not significant), indicating that the marginal institutional effect is absorbed into the persistence mechanism at the highest concentration levels.

4.4 AgriStack Difference-in-Differences and Generalized Synthetic Control

Table 5 reports causal estimates of the effect of AgriStack Farmers' Registry activation on sugarcane acreage share. Two estimators are presented: the two-way fixed effects DiD (TWFE) and the Generalized Synthetic Control (GSC) estimator of Xu (2017), implemented via the gsynth package. The GSC extends the synthetic control method to panel data with multiple treated units by modelling unobserved time-varying confounders through an interactive fixed effects structure with the number of factors selected by cross-validation.

Table 5
AgriStack Difference-in-Differences and Generalized Synthetic Control results

A. Pre-treatment placebo (TWFE)	Estimate	SE	p-value
Lead-2 (t − 2 pre-treatment)	0.059	0.038	0.127
Lead-1 (t − 1 pre-treatment)	0.036	0.036	0.328
B. Treatment effects			
ATT (overall, TWFE)	−0.037	0.022	0.088
ATT (Cohort 1, n = 6, 2020)	−0.074	0.037	n.r.
ATT (Cohort 2, n = 8, 2021)	−0.015	0.023	n.r.
ATT (GSC, Xu 2017, r = 1)	−0.005	—	—
C. Statistical power			
MDE (α = 0.05, power = 0.80)	0.090	—	—
D. Diagnostics			
N (districts)	34	—	—
Treated / Never-treated	14 / 20	—	—
Year FE	Yes	—	—
District FE	Yes	—	—

*Note: Outcome variable: district-year sugarcane acreage share. TWFE = two-way fixed effects estimator with district and year fixed effects. GSC = Generalized Synthetic Control (*Xu, 2017*), implemented via gsynth package; r = 1 latent factor selected by cross-validation. SE = cluster-robust standard errors at district level (HC1) for TWFE; GSC SE not reported (inference via bootstrap in parametric mode). MDE = minimum detectable effect at α = 0.05, power = 0.80. Pre-treatment leads: β(lead-1) = 0.036 (p = 0.328); β(lead-2) = 0.059 (p = 0.127). Cohort 1 (2020): Ahmednagar, Jalgaon, Latur, Nashik, Pune, Yavatmal. Cohort 2 (2021): Aurangabad, Buldhana, Dhule, Hingoli, Nagpur, Nanded, Osmanabad, Washim. Never-treated control: 20 districts. n.r. = p-value not reported (cohort-level SE computed via separate TWFE, not cluster-bootstrapped). Controls: irrigation share, rainfed share.*

Pre-treatment validity is confirmed by two placebo tests. The TWFE lead coefficients are lead-1 = 0.036 (SE = 0.036, p = 0.328) and lead-2 = 0.059 (SE = 0.038, p = 0.127), both statistically indistinguishable from zero. The GSC pre-treatment ATTs range from − 0.005 to + 0.016 across the four pre-treatment periods, with a mean of + 0.004, confirming no systematic pre-trend.

The TWFE estimator yields an average treatment effect of − 0.037 (SE = 0.022, p = 0.088). The cohort-specific estimates are − 0.074 (SE = 0.037) for Cohort 1 (activation year 2020, n = 6 districts: Ahmednagar, Jalgaon, Latur, Nashik, Pune, Yavatmal) and − 0.015 (SE = 0.023) for Cohort 2 (activation year 2021, n = 8 districts: Aurangabad, Buldhana, Dhule, Hingoli, Nagpur, Nanded, Osmanabad, Washim). Both cohorts are directionally consistent and negative. The minimum detectable effect at α = 0.05 and power of 0.80 is 0.090, exceeding the absolute ATT of 0.037. The null result is uninformative about effects smaller than 9 percentage points of acreage share.

The GSC estimator selects one interactive fixed effect factor via cross-validation (r = 1), controlling for one unobserved time-varying confounder that TWFE cannot absorb. The GSC average ATT is − 0.005, smaller in magnitude than the TWFE estimate and closer to zero, reflecting the additional confounder control. The year-by-year GSC ATTs are: −0.010 (year 0), − 0.002 (year + 1), − 0.005 (year + 2), − 0.010 (year + 3). Both estimators are directionally consistent and confirm that AgriStack activation did not produce a detectable positive reallocation away from sugarcane in Maharashtra districts during 2020–2022. The result is consistent with the coordination mechanism: information provision about alternative crop prices does not change whether mill viability depends on aggregate cane supply, leaving the individual incentive structure intact.

4.5 Robustness

Table 6 reports three robustness specifications. The first excludes the five Konkan coastal districts (Ratnagiri, Sindhudurg, Raigad, Thane, Palghar) where sugarcane cultivation is structurally absent due to laterite soils and horticulture-dominated land use. The second restricts the sample to the pre-COVID period 2016–17 to 2019–20. The third retains the binary GPI indicator alongside log mill density to verify that the continuous dose-response is not an artefact of the log transformation.

Table 6
Robustness checks: mill density and persistence across alternative specifications

Specification	Log mills	Lag share	SPI3+	SPI3−	R^2
Baseline (N = 238, Time FE)	0.047**	0.675***	−0.047	0.055.	0.741
Excl. Konkan districts (N = 203)	0.039*	0.922***	0.008	0.027	0.813
Pre-COVID 2016–17 to 2019–20 (N = 136)	0.047**	0.625***	−0.028	0.035	0.738

*Note: Dependent variable: district-year sugarcane acreage share. All specifications include year fixed effects and cluster-robust standard errors at the district level (HC1). *** p < 0.01, ** p < 0.05, * p < 0.10,. p < 0.15. Baseline corresponds to Model A in* Table 3. *Konkan districts excluded: Ratnagiri, Sindhudurg, Raigad, Thane, Palghar. SPI3 + and SPI3 − included in all specifications. R^2 is the within R^2.*

The log mill density coefficient is positive and significant across all three specifications. The lagged share coefficient remains above 0.620 in all specifications and above 0.900 in the Konkan-excluded sample, where the removal of zero-sugarcane coastal districts sharpens the within-sample persistence signal. The pre-COVID specification (GPI = 0.166, lag = 0.625) is virtually identical to the baseline, confirming that the findings are not driven by the COVID-19 agricultural disruption years of 2020–21 and 2021–22. The binary GPI coefficient when included alongside log mill density is positive but reduced in magnitude, consistent with the continuous mill density variable capturing a richer characterisation of the institutional gradient than the binary indicator.

4.6 Welfare implications

The coordination amplification result carries a direct welfare implication. Districts with the highest mill density show near-complete or super-unit persistence in sugarcane allocation. Panel quantile regression confirms that persistence at Q90 exceeds 1.07. These districts are growing more concentrated in a water-intensive crop in a water-scarce environment each year, not merely maintaining concentration. The aggregate welfare cost is not simply the forgone returns from alternative crops but the externality imposed on groundwater users outside the coordination equilibrium.

Taluka-level evidence from the Socio-Economic Survey of Solapur District 2024–25 (Jilha Sankhyiki Karyalay Solapur, Government of Maharashtra) illustrates the within-district dimension of the coordination mechanism. Pandharpur and Malshiras, the two talukas with the highest cooperative mill density in Solapur, reported 67,164 hectares under sugarcane and 9,731 hectares under jowar in 2024–25, a sugarcane-to-jowar ratio of 6.9:1. Barshi and Akkalkot, the two talukas without significant cooperative mill presence, reported 27,559 hectares under sugarcane and 98,902 hectares under jowar, a ratio of 0.28:1. The within-district contrast is 24.6 times. Solapur receives 759 mm of mean annual rainfall. Sugarcane requires 2,000 to 2,500 mm of water annually. The coordination trap sustains a crop whose water demand exceeds rainfall availability by a factor of three in the talukas where coordination is strongest. Net irrigated area in Solapur district rose from 324,500 hectares in 2011 to 445,800 hectares in 2023, documenting the groundwater extraction externality that the coordination equilibrium imposes on all aquifer users in the district.

Table 7
Within-district welfare contrast: Solapur taluka-level crop allocation, 2024–25

Taluka group	Sugarcane (ha)	Jowar (ha)	Ratio (sg:jr)	Institutional context
Pandharpur + Malshiras (cooperative belt core)	67,164	9,731	6.9:1	Highest mill density in district; FRP procurement guaranteed
Barshi + Akkalkot (non-cooperative talukas)	27,559	98,902	0.28:1	No cooperative mill presence; market-rate price exposure
Sangola + Mangalwedha (transitional talukas)	15,948	27,477	0.58:1	Partial cooperative presence; intermediate concentration
Solapur district total	188,307	234,077	0.80:1	District receives 759 mm rainfall; sugarcane needs 2,000–2,500 mm

*Note: Crop areas in hectares. Source: Socio-Economic Survey of Solapur District 2024–25 (Jilha Sankhyiki Karyalay Solapur, Government of Maharashtra). Sugarcane-to-jowar ratio computed as Sugarcane_ha / Jowar_ha. Mean annual rainfall in Solapur district: 759 mm (IMD, 2023). Sugarcane water requirement: 2,000–2,500 mm per season (*ICAR-Sugarcane Breeding Institute, 2021*). Net irrigated area rose from 324,500 ha (2011) to 445,800 ha (2023), documenting groundwater extraction externality associated with the coordination equilibrium. (P) = provisional.*

The Small Farmer interaction finding from Section 4.2 adds a distributional dimension. Districts with higher smallholder shares show stronger sugarcane concentration (SmallFarmer = 1.738, p = 0.039 in Model B). Small farmers depend most heavily on cooperative input credit and guaranteed procurement. Their participation sustains the coordination equilibrium but simultaneously locks them into a water-intensive crop

in drought-vulnerable districts. The coordination trap is not welfare-neutral across farm size: it is most binding precisely for the farmers with the fewest resources to absorb a transition to alternative crops.

5. Discussion

5.1 The coordination trap interpretation

Three predictions of the coordination game framework are tested in Section 4. Two are confirmed. The dose-response relationship between cooperative mill density and sugarcane acreage share (Prediction 1) is confirmed: log_mills = 0.047 ($p = 0.005$), with a monotonic gradient from zero at zero mills to 13.2 percentage points at 16 mills. The persistence amplification result (Prediction 2) is confirmed: the interaction coefficient log_mills × lag = 0.223 ($p < 0.001$) establishes that institutional density raises year-on-year persistence continuously, from 34.4 per cent at zero mills to 101.1 per cent at 19 mills. The information provision null result (Prediction 3) is confirmed: the TWFE ATT of − 0.037 and the GSC ATT of − 0.005 are both negative and small, with neither estimator detecting a positive reallocation away from sugarcane following AgriStack activation.

The bimodality prediction, a fourth implication of the coordination game that was tested but not reported as a primary prediction, is not supported. The Hartigans dip test gives $p = 0.935$ at the district mean level, indicating a unimodal distribution. The absence of bimodality does not invalidate the coordination interpretation. The distribution is right-skewed with a thin upper tail rather than bifurcated, reflecting the continuous variation in mill density across Maharashtra districts. A perfectly bifurcated distribution would require a sharper institutional discontinuity than the one observed. The continuous dose-response and persistence amplification results are more informative than a bimodality test and do not require bifurcation.

The panel quantile regression adds a dimension that mean regression conceals. Persistence at Q90 is 1.073, exceeding unity. Districts in the upper tail of the sugarcane share distribution are not in a self-sustaining equilibrium but in a self-amplifying one. The coordination equilibrium at the highest institutional density levels generates positive feedback: each year of sustained concentration deepens farmer-mill relationships, specialises the input market, and raises the individual cost of deviation. This intensification is not captured by the mean coefficient of 0.675 and distinguishes the coordination mechanism from a simple switching-cost story, under which persistence would be bounded below unity.

5.2 Alternative explanations

Three alternative explanations for the dose-response and persistence findings deserve explicit consideration. First, irrigation access. Cooperative belt districts may have better irrigation infrastructure, making sugarcane cultivation physically feasible independently of the procurement guarantee. The irrigation share coefficient is statistically insignificant in all specifications ($p = 0.252$ in Model A, $p = 0.331$ in Model B), and the Solapur taluka within-district contrast shows a 24.6-times gap in the sugarcane-to-jowar ratio between high-mill and low-mill talukas within the same district, where irrigation access differences are smaller than across districts. The irrigation channel does not account for the observed pattern.

Second, soil type and agro-climatic suitability. Cooperative belt districts in western Maharashtra have Vertisol soils more suited to sugarcane than the Alfisol-dominant soils of Vidarbha. Soil suitability is a time-invariant district characteristic absorbed by time fixed effects in the cross-sectional identification. The dose-response within Maharashtra's 34 districts after time demeaning is difficult to attribute solely to soil variation, given that the gradient maps precisely onto mill count rather than soil class boundaries. The robustness specification excluding Konkan coastal districts, where soil and topography diverge most sharply from the agricultural interior, yields a GPI coefficient virtually identical to the baseline.

Third, political economy of mill licensing. Districts with more mills may have historically stronger cooperative political networks that lobby for input subsidies, water allocation priorities, and price support. If political economy and mill density are correlated, the mill density coefficient partially reflects political economy effects rather than the coordination mechanism. This channel cannot be fully ruled out with the current data. The interaction result partially addresses this concern: if political economy were the primary channel, persistence should be proportional to political influence regardless of prior sugarcane history. The interaction term $\gamma_3 = 0.223$ shows that mill density amplifies persistence specifically through the lagged share, consistent with the coordination mechanism and less consistent with a pure political economy interpretation.

5.3 Comparison with existing literature

Liu (2013) estimates a loss aversion coefficient of 1.50 to 2.50 for Chinese corn farmers using individual-level adoption data. Bocquého et al. (2014) estimate $\lambda = 1.72$ for French cereal farmers using experimental elicitation. The current paper does not recover individual-level loss aversion parameters from district-aggregate data, a deliberate methodological choice motivated by the aggregation problem documented by

Ai and Norton (2003) and discussed in Section 3. The coordination game framework used here makes a different and more empirically tractable claim: that the institutional guarantee shifts the effective certainty premium, making sugarcane the risk-dominant strategy under any positive history of cooperative belt participation. This is a reduced-form statement about aggregate behaviour that does not require recovering individual CPT parameters.

Foster and Rosenzweig (1995) document social learning in technology adoption among Indian farmers. Munshi (2004) shows that social network density accelerates HYV wheat adoption in Indian districts. The persistence coefficient of 0.675 at the mean and 1.073 at Q90 is consistent with social observation operating alongside institutional lock-in: farmers observe neighbours' sugarcane choices and update beliefs about the mill's viability and the guarantee's reliability. The two channels, institutional coordination and social learning, are empirically indistinct at the district-year level and are treated as complementary in this analysis.

6. Policy Implications

6.1 Procurement certainty as the binding constraint

The dose-response finding (log_mills = 0.047, p = 0.005) establishes that the number of cooperative mills in a district, not irrigation access, average holding size, or rainfall variability, is the primary predictor of sugarcane concentration after controlling for year effects. Each doubling of the cooperative mill count adds 3.2 percentage points to sugarcane share. The policy implication is precise: crop diversification in cooperative belt districts requires addressing the procurement certainty asymmetry between sugarcane and alternative crops. The FRP is legally mandated and enforceable. The MSP for tur, gram, and jowar is announced but not procurement-guaranteed at the district level. Extending a legally enforceable procurement guarantee to one or two alternative crops in high-mill-density districts would directly address the certainty premium that sustains the coordination equilibrium.

A Tur or Soybean Producer Company with pre-season procurement contracts at an announced floor price, backed by a legal enforcement mechanism analogous to the Sugar Act's FRP provisions, would create a competing coordination device. Farmers in Vidarbha and Marathwada districts with zero or low cooperative mill counts already grow tur and soybean without such a guarantee. The marginal farmer in a high-mill district faces a coordination payoff that no price signal can override: switching individually does not improve the mill's catchment and incurs the full switching cost. A coordinated procurement guarantee for an alternative crop would shift the coordination equilibrium at the catchment level rather than incentivising individual deviation.

6.2 Why digital information provision is insufficient

The AgriStack null result carries a specific policy implication. The TWFE ATT of − 0.037 and the GSC ATT of − 0.005 establish that AgriStack activation in Maharashtra districts from 2020 to 2022 produced no detectable positive reallocation toward alternative crops. The Cohort 1 ATT of − 0.074 indicates that the first cohort of adopting districts, with more complete farmer registration and longer exposure to the system, shows a slightly larger negative effect. The null result does not reflect a design failure in AgriStack. It reflects a mechanism failure: the programme provides market price information and digitises land records, neither of which changes N_j relative to N^* or alters the individual payoff to deviation from the coordination equilibrium.

India's Digital Agriculture Mission has positioned AgriStack as a foundational infrastructure for crop diversification, market linkage, and farmer welfare. The current evidence suggests that this positioning is premature in settings where the binding constraint is institutional rather than informational. Farmers in high-mill Maharashtra districts are not uninformed about alternative crop prices. They face a coordination problem that information cannot dissolve. The MDE of 0.090 exceeds the absolute ATT of 0.037, so small informational effects below 9 percentage points cannot be excluded. For policy purposes, the relevant question is whether informational effects of this magnitude would constitute a meaningful contribution to Maharashtra's crop diversification agenda, given that the coordination equilibrium generates a 15-to-16 percentage point institutional premium in the opposite direction.

6.3 Small farmer welfare and the coordination trap

The SmallFarmer coefficient of 1.738 (p = 0.039) in Model B indicates that districts with higher smallholder shares show greater sugarcane concentration when mill density amplifies persistence. Small farmers are the most dependent on cooperative input credit, pre-season procurement contracts, and the certainty premium that the mill provides. Their participation is individually rational given their resource constraints and credit access but collectively sustains the coordination equilibrium in a water-scarce environment. The welfare implication is that crop diversification policies targeting small farmers in cooperative belt districts must address credit access and income certainty simultaneously. A policy that removes the cooperative procurement guarantee without providing a comparable alternative for small farmers would impose a disproportionate welfare cost on the most vulnerable participants in the coordination equilibrium.

The Solapur taluka contrast illustrates the distributional dimension concretely. In Pandharpur and Malshiras, where 67,164 hectares of sugarcane coexist with 9,731 hectares of jowar, the majority of small farmers are embedded in cooperative supply chains that provide input credit, transportation, and guaranteed payment. In Barshi and Akkalkot, where 98,902 hectares of jowar coexist with 27,559 hectares of sugarcane, small farmers face open market price risk without equivalent institutional support. Extending cooperative-style procurement certainty to jowar or tur in the Barshi-Akkalkot cluster would target the correct constraint for the correct beneficiary group.

7. Conclusion

7.1 Summary of findings

This paper examines why Maharashtra's cooperative-belt districts maintain sugarcane concentration at 8.8 times the level of non-cooperative districts across seven Kharif seasons despite price signals, insurance incentives, and digital agricultural information provision that would, under standard rational choice assumptions, induce diversification. Three findings emerge from a four-method empirical analysis using 238 district-year observations built from verified government administrative data.

First, cooperative mill density has a continuous dose-response relationship with sugarcane acreage share. Each doubling of the cooperative mill count is associated with a 3.2 percentage point increase in sugarcane share (log_mills = 0.047, SE = 0.016, p = 0.005). The gradient is monotonic from zero mills (no premium) to 19 mills in Kolhapur (13.97 percentage points). This dose-response is the paper's primary identification contribution: it exploits continuous within-Maharashtra variation in institutional density rather than a binary belt classification.

Second, mill density amplifies year-on-year acreage persistence through a coordination mechanism. The interaction coefficient log_mills × lag = 0.223 (SE = 0.047, p < 0.001) establishes that institutional density raises persistence continuously from 34.4 per cent at zero mills to 101.1 per cent at 19 mills. Panel quantile regression (Canay, 2011) reveals that persistence exceeds unity at the 90th percentile of the district sugarcane distribution, confirming self-amplifying coordination dynamics in the most institutionally embedded districts. These findings are consistent with a stag hunt coordination game in which mill viability depends on aggregate cane supply, making individual deviation individually irrational regardless of price signals.

Third, AgriStack digital agriculture programme activation did not produce a detectable reallocation away from sugarcane. The TWFE ATT is − 0.037 (SE = 0.022, p = 0.088) and the Generalized Synthetic Control ATT (Xu, 2017) is − 0.005 (optimal r = 1 factor), both directionally consistent null results. Parallel trends is validated by insignificant pre-treatment lead coefficients. The null result is consistent with the coordination game prediction: information about alternative crop prices does not change N_j relative to N* and leaves the individual payoff structure intact.

7.2 Theoretical contribution

The paper makes one conceptual contribution to the literature on agricultural technology and institutional adoption. It formalises the coordination game mechanism through which cooperative procurement guarantees sustain crop allocation inertia, demonstrating that the institutional effect operates through persistence amplification rather than a level shift. The interaction specification γ_s[log(1 + mills) × lag] identifies this amplification as a continuous dose-response, distinguishing the coordination channel from switching costs (which would generate bounded persistence) and political economy (which would not generate the lagged share specificity). The quantile regression gradient from Q25 = 0.825 to Q90 = 1.073 extends this contribution by showing that the coordination trap intensifies at the upper tail of the distribution, a result that mean regression cannot reveal.

7.3 Limitations and future research

Four limitations bound the scope of this study's conclusions. First, the log mill density variable is sourced from the current cooperative factory registry and does not capture temporal variation in mill openings and closures during the study period 2016–17 to 2022–23. A panel of mill-level operational status by year would enable a more precise identification of the coordination mechanism using mill entry and exit as treatment events. Second, the analysis operates at the district-year level. Individual-level verification of the coordination payoff structure requires farmer-level data on mill contract status, input credit access, and crop choice history, which are not publicly available for Maharashtra at annual frequency during the study period. Third, the minimum detectable effect of 0.090 for the AgriStack DiD exceeds the estimated ATT of 0.037 in absolute value. A longer post-treatment window extending to 2025–26, as AgriStack registration matures, would provide a more powerful test of informational effects. Fourth, the welfare analysis relies on a single-year cross-section from the Solapur District Socio-Economic Survey 2024–25. A longitudinal taluka-level panel would enable a causal welfare estimation rather than the illustrative within-district contrast reported here.

Three directions for future research follow directly from the coordination game framework. The mill viability threshold N* is treated as a structural parameter in the theoretical exposition but is not estimated. Identifying N* from observational data requires panel variation in mill

catchment boundaries over time, which may be available from Sugar Commissionerate season-wise records with a more granular data request. The positive feedback dynamics at Q90, where persistence exceeds unity, raise the question of whether the coordination equilibrium in high-mill districts is stable or diverging. A longer panel extending beyond 2022–23 would allow testing whether concentration at Q90 is reaching a natural ceiling or continuing to intensify. The welfare cost of the coordination trap for groundwater resources is documented descriptively using Solapur irrigation data but not quantified causally. A spatial regression discontinuity exploiting variation in canal command area boundaries within Solapur district would identify the causal effect of irrigation access on sugarcane concentration net of the coordination mechanism.

Declarations

Conflict of Interest

The author declares no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data Availability

The analysis dataset (238 observations), variable codebook (RODE_01_Codebook.R), data construction script (RODE_02_Build_Dataset.R), and estimation script (RODE_03_Estimation.R) have been deposited on Mendeley Data at https://doi.org/10.17632/2y4fb7hd7h.1 (Vhankade, 2026) and are available to reviewers on request via a private share link. The underlying administrative data are publicly accessible through Indian government portals documented in the README file (RODE_04_README.txt). The compiled dataset is available from the corresponding author on reasonable request at prakash.vhankade@gipe.ac.in.

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