# Beyond Yields: How Climate Change Affects Farmers Through Market Structure*

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**Abstract**

Climate change hurts farmers by lowering crop yields. In this paper, I show that it also hurts farmers by changing the structure of the markets they sell in. To document this, I exploit extreme drought shocks in the water-intensive Indian sugar industry where 8M smallholders sell perishable cane to oligopsonistic sugar mill intermediaries. I assemble a newly digitized 35-year administrative panel on the universe of Indian sugar mills, and a georeferenced farmer-mill transaction panel on 3M cane farmers. Using a staggered event study design, I show that droughts concentrate markets by removing the least productive mills, and trigger long-term productivity growth within survivors through management upgrading. Yet farm-gate cane prices fall as these gains are captured by survivors through increased buyer power. Reduced cane prices account for one half of farmers' long-term income losses — on par with yield losses themselves — pointing to a large role for market structure in shaping farmers' climate burden. To quantify aggregate welfare impacts, I build and estimate an equilibrium model of the Indian sugar sector that embeds a management upgrading choice for sugar mills. Drought-induced market restructuring raises aggregate mill productivity by 12 percent through both selection and within-firm channels, but long-term farmer welfare declines by 8 percent as markdowns widen.

**Keywords:** market structure, climate, agriculture, firm productivity, oligopsony, sugar
**JEL Codes:** L11, L13, L66, O13, Q13, Q54

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# 1 Introduction

A large and compelling literature documents that climate change imposes significant costs on farmers by lowering crop yields.[1] Even after accounting for farmer adaptation, global average yields are projected to decline by more than 20% by the end of the century (Hultgren et al., 2025). These impacts are expected to be felt most acutely in low-income countries where a large share of the population is still reliant on agriculture.[2] Crop yields, however, form only one part of the story when it comes to farmer welfare. What farmers earn also depends on the prices they receive for their harvest, which are typically set in markets comprising a small number of intermediaries such as traders, agribusinesses or processors.[3] A growing literature shows that these intermediaries wield substantial buyer power over farmers by significantly marking down the prices they pay below what a competitive market would deliver (Chatterjee, 2023; Rubens, 2023; Zavala, 2026; Dominguez-Iino, 2026). Prices that farmers receive are, therefore, intrinsically tied to their local market structure.

Crucially, this market structure is not fixed because intermediaries are themselves exposed to climate change, and their response impacts the prices that farmers receive. For example, a severe climate shock can push the weakest intermediaries to exit, handing greater buyer power to the ones that survive.[4] Similarly, a rise or fall in their productivity can shift demand for inputs and move prices in either direction. Changes in local market structure can therefore either cushion farmers' losses or compound them. Yet we know little about how agricultural markets adjust in response to climate events, and how these adjustments impact farmer welfare. Filling this gap has been especially difficult because changes in long-term market structure and prices are rarely observed. This motivates the central question of the paper: How economically significant is climate-induced restructuring of agricultural markets for long-term farmer welfare?

I take this question to the Indian sugar industry, which is the world's second largest, and produces a fifth of all sugar worldwide. In this setting, farmers sell perishable cane to local sugar mill intermediaries that produce sugar and supply downstream consumer markets. Contributing roughly 2% to India's overall GDP, the sugar sector occupies an important position in India's agricultural and industrial landscape, with 8 million smallholder farmers growing cane and 0.5 million workers employed in its 550

[1] Some of the earlier seminal works include Mendelsohn, Nordhaus and Shaw (1994); Schlenker and Roberts (2009); Lobell, Schlenker and Costa-Roberts (2011)

[2] See Dell, Jones and Olken (2012); Burke, Hsiang and Miguel (2015); Carleton et al. (2022)

[3] Traders have been documented by Bergquist and Dinerstein (2020) and Chatterjee (2023) in Kenya and India; Dhingra and Tenreyro (2026), Zavala (2026) and Dominguez-Iino (2026) study agribusinesses in six countries across Africa and South America; Avignon and Guigue (2025) and Rubens (2023) look at processors in France and China.

[4] Kochhar, Song and Sun (2024) find that higher oligopsony power in agricultural markets also blunts farmers' own capacity to adapt due to lower input usage in anticipation of lower farm-gate prices.

sugar mills. However, climate change has emerged as a real threat, in particular, due to cane's extreme water-intensity, which makes the sector highly sensitive to droughts.[5]

Droughts are a direct consequence of meteorological and hydrological conditions such as failures of the summer monsoon, elevated temperatures that raise evapotranspiration, and the depletion of soil moisture, all of which are likely exacerbated in frequency and severity by climate change. The timing of these events is arguably exogenous to local industry characteristics. Many of the most severe episodes are driven by El Niño events, which are also projected to intensify in a warming world.[6] I focus on extreme, 1-in-50-year drought events because they are severe enough to alter market structure through *direct effects* on farmers, via lower cane yields, and *indirect effects* on sugar mills, via disruptions to local supply chains.

Two features make the Indian sugar setting an ideal laboratory for this paper. First, perishability of cane ties farmers to nearby mills and creates localized markets, with the median cane sale at a distance of only 13 km from a mill. This spatial concentration gives mills oligopsony power and allows me to partition cane-growing regions into distinct markets. Second, different markets experience droughts in different years, which gives quasi-experimental variation in where and when the shock lands, and in how it reshapes local market structure. Because these features characterize agricultural supply chains across a wide range of commodities and geographies[7], the paper's findings promise to be relevant for settings beyond Indian sugar.

In this paper, I make four contributions. First, I newly digitize a novel 35-year administrative panel on the universe of all sugar mills in India and supplement it with a georeferenced farmer-mill transaction panel on 3 million cane farmers and a survey of 220 sugar mills. This data allows me to document the structure and evolution of cane markets throughout India on an unprecedented scale. Second, exploiting spatial and temporal variation in extreme drought events, I provide empirical evidence that exposure to droughts causes the least productive sugar mills to exit, and their farmers to reallocate to nearby survivors. These surviving mills reorganize their labour and improve cane quality management, allowing them to observe long-term productivity gains. Strikingly, within-mill cane prices see a decline indicating that internal productivity gains are captured by surviving mills through amplified markdowns.

[5] Recent reporting underscores the stakes: the 2026 El Niño-induced drought is bound to cause large losses to India's cane output. See *The New York Times*, 16 October 2026, https://www.nytimes.com/2026/10/16/climate/india-sugarcane-production-sugar-prices.html.

[6] See Cai et al. (2014); Callahan and Mankin (2023); Cole et al. (2026); Kikstra et al. (2022); Kumar et al. (2006); Wang et al. (2017); Xue et al. (2025)

[7] See Macchiavello and Morjaria (2021); Leone et al. (2025) for coffee in Rwanda and Costa Rica; Bergquist and Dinerstein (2020) for maize in Kenya; Rubens (2023) for tobacco in China; Zavala (2026) for cash crops in Peru; Avignon and Guigue (2025) for dairy in France

Third, to rationalize the patterns in the event studies and quantify aggregate welfare impacts, I develop an equilibrium framework of the Indian sugar sector. I combine a nested discrete choice system for farmers — who choose among crops and among sugar mills if they grow cane — with oligopsonistic pricing among mills who also make a management upgrading choice. Fourth, I estimate this model using mill-level and farmer-level data to quantify how drought-induced selection and within-mill productivity growth contribute to aggregate productivity gains among sugar mill intermediaries. More importantly, I estimate how changes in market structure triggered by a transient drought shock impact long-term farmer welfare.

To examine how extreme droughts reshape local market structure and impact cane farmers, I assemble several novel datasets that allow me to link sugar mill operations and farm-gate prices with drought exposure. First, I digitize archival records from the Indian Directorate of Sugar, which document comprehensive information on procurement, production, and managerial and technological practices for the universe of Indian sugar mills from 1990 to 2025. Second, through a close partnership with the Sugar Commissionerate in Maharashtra – India's largest sugar producing state – I obtain first-time access to a georeferenced panel on farmer-mill transactions covering all 3 million cane farmers in the state from 2020 to 2025. Third, I conduct a survey of 220 sugar mills in Maharashtra and elicit information on drought risk, farmer-mill relationships and climate adaptation investments. Next, I link these administrative records to each mill's financial data from 1993 to 2023 using common identifiers with the Annual Survey of Industries (ASI). This allows me to identify, for the first time, every plant in the ASI for a large and important industry.[8] Finally, I construct Standardized Precipitation Evapotranspiration Indices (SPEI) – my primary measure of extreme droughts – for each market-year, using high resolution data from the Drought Atlas of India (Chuphal et al., 2024).

Using this combined data, I document three stylized facts that directly motivate my empirical strategy and findings. First, trade in cane is highly localized, giving rise to spatially segmented markets. Nearly 80% of all trade occurs within 25 km of a mill location and virtually all trade exhausts within 50 km. This is because cane's sugar content deteriorates rapidly after harvest, leaving mills with only a 12–18 hour window to process it. Second, mills have price-setting power over farmers in these local cane markets but behave as price-takers in the sugar market. This is driven by policy wherein the central government tightly controls mill-level sugar releases to stabilize consumer prices. Third, mills differ enormously in observed productivity, measured by sugar recovery. The most productive mills extract more than twice as much sugar from a given quantity of cane as the least productive, who also earn thinner margins

[8]The ASI does not disclose plant names or any identifier other than an anonymous plant ID.

per tonne of cane crushed. This makes the least productive mills most vulnerable to extreme droughts, setting the stage for my empirical strategy and results.

My empirical strategy exploits spatial and temporal variation in extreme drought events which correspond to SPEI values lower than -2. To quantify market- and mill-level adjustments to droughts, I implement an event-study design using the Sun and Abraham (2021) estimator to address concerns about heterogeneous treatment effects in staggered difference-in-differences settings. The empirical results reveal four key findings. First, extreme droughts concentrate markets by triggering the exit of least productive sugar mills and the reallocation of their farmers to nearby survivors. Marginal survivors who run shorter seasons at baseline and are therefore capacity-unconstrained relative to productive survivors absorb this reallocated cane. Second, these marginal survivors that see a rise in scale improve cane quality management practices. This allows them to raise sucrose content in procured cane and observe a 5 percent increase in sugar recovery – the observed measure of productivity – over the subsequent decade. Third, and strikingly, within-mill cane prices do not change for marginal survivors despite recovery gains, while capacity constrained productive survivors see a 5% decline in their cane prices, suggesting amplified oligopsony power in cane markets. A decomposition of aggregate impacts on farmer cane income into a *yield* component and a *price* component reveals that reduced cane prices explain one half of farmers' income losses – on par with yield losses themselves. Together, these results point to a large role for market structure, a previously unexplored channel, in shaping farmers' long-term climate burden.

To interpret these findings, I develop and estimate an equilibrium model of the Indian sugar sector that links sugar mills' demand for cane with upstream farmer supply. On the demand side, I model sugar mills as oligopsonists and embed capacity constraints and a management upgrading choice in their optimization problem. I define their production function using a Leontief technology to account for the fact that cane cannot be substituted with either labour or capital in order to produce sugar. Departing from the common assumption that the conversion rate of intermediate input to output is homogeneous (Rubens, 2023; Avignon and Guigue, 2025) and exogenous (De Loecker and Scott, 2016), I treat sugar recovery – the conversion factor in my setting – as a mill-level choice increasing in cane management upgrading. This structure yields the paper's two central comparative statics that explain the event-study results. First, upgrading benefit is increasing in cane volume. This complementarity between scale and upgrading explains how a reallocation-induced rise in scale of marginal survivors drives their recovery growth. Second, the benefit also scales with the share of captured value, which is larger when residual supply is less elastic. So, the same restructuring that raises a survivor's scale also raises the share of the upgrading gain it retains. I run

several falsification tests that rule out competing explanations, and confirm that sugar recovery gains operate through scale-driven management-upgrading.

On the supply side, I model farmer decisions using a nested discrete-choice framework that captures two margins of adjustment. In the outer nest, a farmer chooses which specific agricultural commodity to grow. In the inner nest, a farmer growing cane chooses which mill to sell to, with choice shaped by the offered price, and observed mill characteristics. This nested structure generates an own-price supply elasticity with two margins – cross-mill substitution (stealing farmers from rival mills) and cross-crop substitution (pulling farmers into cane from alternative crops). This elasticity carries the paper's market-power mechanism: when droughts increase market concentration through mill exit and farmer reallocation, a surviving mill's within-cane share rises, its residual supply becomes less elastic, and its markdown widens.

Estimation proceeds in two stages. First, I estimate the production function using a control-function approach with endogenous exit (Olley and Pakes, 1996; Ackerberg, Caves and Frazer, 2015). To address the Doraszelski and Jaumandreu (2021) critique that input demand may shift due to either productivity or markdowns, I use the nested farmer supply model to control for markdown variation with observed prices of sugar and cane, and mill-level market shares, thereby restoring the scalar-unobservable assumption. Next, I estimate the supply elasticities using crop-level and mill-level shares with instruments for prices. As expected, I find that mills are closer substitutes for one another than cane is for competing crops, suggesting substantial crop switching costs. I also find the cross-crop elasticity estimate to be in line with values from the agricultural trade literature.[9]

The estimates reveal that sugar mills hold considerable buyer power over farmers: the average mill paid its farmers 83% of the marginal revenue product of cane. This markdown level is comparable with figures obtained for other agricultural goods in the literature.[10] Using the estimated TFP and cane price markdowns, I examine how drought-induced market restructuring affected both mill productivity and buyer power. I find that droughts increased within-mill TFP by 12 percent on average, compared to a 5 percent rise in sugar recovery (equivalently, the marginal product of cane) documented earlier. Droughts also led to increased exertion of oligopsony power in cane markets: markdowns increased on average by 5-6 percent, a decade after the shock.

Next, I use the model to quantify the impact of extreme droughts on aggregate mill

[9] My estimated value of 2.12 sits in between the range of 1.5-2.5 documented in Sotelo (2020); Bergquist and Dinerstein (2020); Costinot, Donaldson and Smith (2016); Dominguez-Iino (2026).

[10] Average inverse markdowns in Avignon and Guigue (2025); Dominguez-Iino (2026); Zavala (2026); Crespi and Sexton (2005) range between 0.66-0.9. My inverse markdown figure of 0.83 falls in the middle of this range.

productivity and farmer welfare. First, I decompose the productivity gains from drought-induced restructuring into a *between-firm* resource reallocation component and a *within-firm* improvement component. Lower cane supply reduces variable profits of mills, pushing the weakest ones into losses. Surviving mills, who inherit farmers from exiting mills, respond by improving management practices and observe a rise in productivity. Mills whose productivity is too low to survive, even with these improvements, exit the market. Both responses – productivity improvements among surviving mills and the exit of unproductive ones – raise aggregate total factor productivity by 12 percent. A decomposition reveals that approximately 90 percent of this increase comes from the exit of low-productivity sugar mills, with the remaining 10 percent stemming from within-firm productivity improvements. I pair this decomposition with a full welfare accounting for both sides of the market, tracing how each channel maps into mill profits and farmer surplus. Mill profits rise by 11.5 percent in the long-term, however cane farmer welfare reduces by 7.8 percent as fewer survivors in more concentrated markets impose wider markdowns on cane prices. This results in an overall welfare loss of 5.1 percent in the long-term.

Taken together, these results reveal a stark distributional fault line in how climate shocks reshape agricultural markets. Drought-induced restructuring raises aggregate mill productivity and mill profits, yet leaves farmers worse off as a more concentrated market turns against them. Climate change does not simply shrink the pie – it redistributes it from farmers to the firms that buy from them, at a net cost to overall welfare.

**Related Literature.** This paper contributes to three literatures: the economics of climate change and agriculture, the study of market power in agricultural value chains, the analysis of how climate and disaster shocks reshape firms and aggregate productivity, and the structural estimation of production functions. Its central contribution is to connect them – to show that the agricultural market structure through which farmers sell is itself an object that climate change reshapes, with first-order consequences for the distribution of welfare.

A large literature quantifies the impact of climate change on agriculture, and establishes that a warming climate harms farmers by lowering the physical productivity of land. This work spans the Ricardian valuation of farmland (Mendelsohn, Nordhaus and Shaw, 1994), climate's effect on agricultural profits (Deschênes and Greenstone, 2007), and the estimation of highly non-linear temperature–yield relationships (Schlenker and Roberts, 2009; Lobell, Schlenker and Costa-Roberts, 2011). A parallel strand studies the margins through which farmers and markets adapt, emphasizing crop switching, technology, and the reallocation of production across space through trade (Burke and Emerick, 2016; Costinot, Donaldson and Smith, 2016; Gouel and Laborde, 2021;

Hultgren et al., 2025; Kochhar, Song and Sun, 2024). Across these approaches, the farmer is modelled as a producer whose welfare is mediated by yields and output prices taken as given, and the market environment in which crops are sold is held fixed. I depart from this literature by showing that climate change harms farmers through a distinct channel that operates *on top of* yields: by restructuring the intermediary markets in which farmers sell. In my setting, the price farmers receive falls even after yields appear to recover, and this market-structure channel accounts for as much of farmers' long-run income loss as the yield channel itself — implying that studies focused on physical productivity alone understate the burden that climate change places on farmers.

Second, the paper speaks to a growing literature on market power in agricultural value chains, which documents that farmers in developing countries sell into thin, imperfectly competitive markets where a small number of intermediaries exercise substantial buyer power. This work has measured oligopsony markdowns and the incomplete pass-through of prices to farmers (Mitra et al., 2018; Bergquist and Dinerstein, 2020; Chatterjee, 2023), shown how competition interacts with the relational contracts that govern these exchanges (Macchiavello and Morjaria, 2021; Macchiavello and Miquel-Florensa, 2017), and embedded buyer power in structural models of crop procurement (Rubens, 2023; Avignon and Guigue, 2025; Dominguez-Iino, 2026; Dhingra and Tenreyro, 2026; Zavala, 2026). This literature, however, largely treats market structure — the number, location, and conduct of buyers — as fixed, and asks what its welfare consequences are. I contribute by identifying climate change as an endogenous driver of market structure, and hence of buyer power. Drought-induced mill exit makes local markets thinner, and the resulting concentration hands surviving mills wider markdowns over farmers. I provide causal, event-study evidence that oligopsony power rises in the aftermath of climate shocks, and use an estimated equilibrium model to quantify how this rising buyer power is passed through to farm-gate prices — adding a dynamic, shock-driven dimension to a literature that has largely studied market power in cross-section.

Third, the paper relates to a literature on how natural disasters and climate shocks affect firms, productivity, and the reallocation of economic activity. This work has traced the propagation of localized shocks through production networks and supply chains (Barrot and Sauvagnat, 2016; Boehm, Flaaen and Pandalai-Nayar, 2019; Castro-Vincenzi, 2022; Pankratz and Schiller, 2024; Castro-Vincenzi et al., 2024; Balboni, Boehm and Waseem, 2026), documented their effects on firm survival and selection (Tanaka, 2015; Basker and Miranda, 2018; Erda, 2024; Cascarano, Natoli and Petrella, 2025), and on firm-level productivity and/or management (Leiter, Oberhofer and Raschky, 2009; Elliott et al., 2019; Zhang et al., 2018; Adhvaryu, Kala and Nyshadham, 2020; Somanathan et al., 2021; Erda, 2024). I add to this literature by showing that a climate shock can *raise* aggregate

productivity in an affected industry, and by decomposing this gain into its two sources: a between-firm selection effect, as the least productive mills exit, and a within-firm effect, as surviving mills respond to their expanded scale by upgrading cane-quality management. Crucially, I connect this productivity response to the market-power channel above: the same restructuring that raises aggregate productivity concentrates procurement and widens markdowns, so that the industry emerges more productive while the farmers who supply it are made worse off.

Finally, the paper contributes methodologically to the estimation of production functions. On the production side, I build on the control function approach to recovering firm productivity (Olley and Pakes, 1996; Levinsohn and Petrin, 2003; Ackerberg, Caves and Frazer, 2015) and on its application to settings with physical output and intermediate inputs. My point of departure concerns the conversion of intermediate input into output. Where much of this literature treats the input-to-output conversion rate as homogeneous across firms (Rubens, 2023; Avignon and Guigue, 2025) or as an exogenous technological parameter (De Loecker and Scott, 2016), I treat sugar recovery — the cane-to-sugar conversion factor in my setting — as a heterogeneous, mill-level *choice* that is increasing in cane quality management. Because recovery and its field- and factory-level components are directly observed in my data, I can separate this chosen conversion margin from Hicks-neutral processing productivity, and let the former respond endogenously to the market environment. This is the key institutional feature of agricultural processing shared by several crops, that a fixed-conversion model omits.

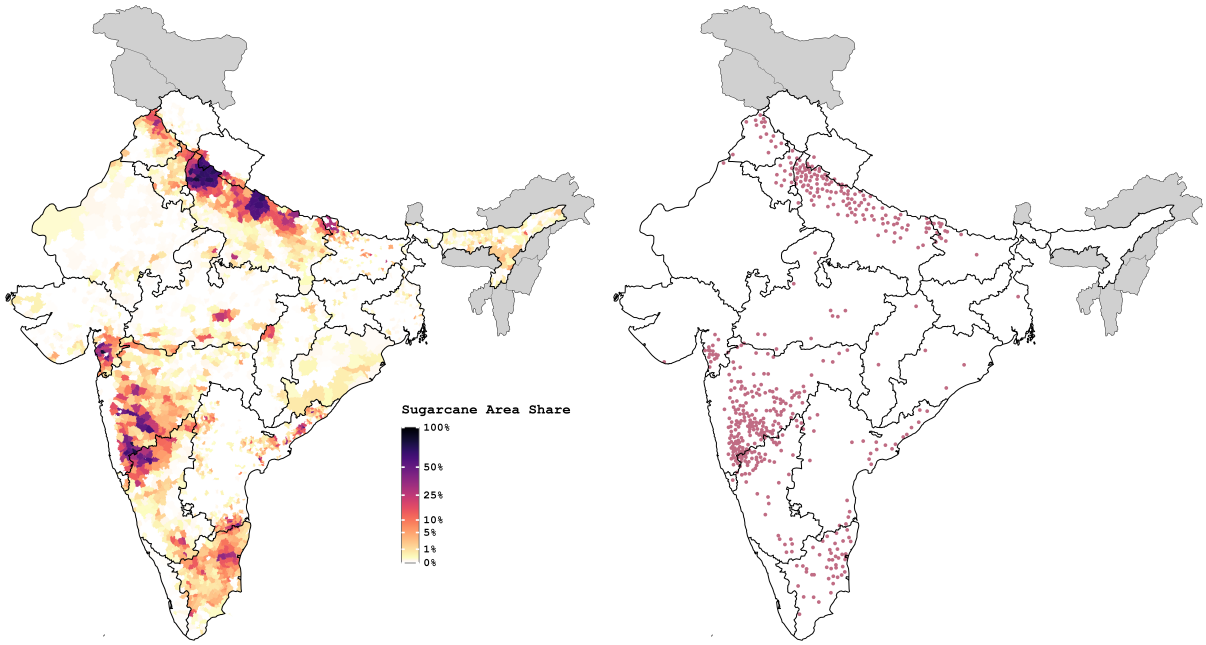
By uniting the firm-productivity and market-power responses to climate shocks within a single equilibrium framework, the paper shows that the efficiency and distributional consequences of climate-driven restructuring cannot be understood in isolation.

The remainder of the paper is organized as follows. Section 2 provides institutional background on the Indian sugar industry. Section 3 describes the data sources and data collection exercise. Section 4 presents motivating stylized facts. Section 5 outlines the empirical strategy and presents the event-study results. Section 6 develops the structural model. Section 7 discusses identification and estimation. Section 8 presents aggregate welfare results. Section 9 concludes.

# 2 Institutional Background

India is the world's second-largest producer of sugar behind Brazil, accounting for a fifth of global production. The industry occupies a central position in the Indian economy — it sources cane from roughly 8 million smallholder farmers, supporting 50 million livelihoods, and directly employs half a million industrial workers.[11] In the process, it contributes to approximately 2 percent of India's GDP. Close to 550 sugar mills intermediaries currently operate in 16 states across the country, although 80% of national sugar output is concentrated in the three major producing states of Maharashtra, Uttar Pradesh and Karnataka. Figure 1 shows the intensity of cane cultivation and location of sugar mills across India in 2015-16.

**Figure 1:** Sugar Production in India




**Panel A:** Cane Cultivation, 2015-16 **Panel B:** Location of Sugar Mills, 2015-16

*Notes:* Panel A shows block-level share of cropped area under cane cultivation in 2015-16. Panel B shows the location of operational sugar mills in India in the 2015-16 season. *Source:* Indian Agriculture Census 2015-16, and plant-level records from the Indian Directorate of Sugar.

## 2.1 The Indian Sugar Value Chain

The Indian sugar value chain is visualized in Figure 2. At the top of the chain, 8 million smallholders cultivate cane on plots averaging 0.8 hectares [12]. These farmers sell their cane to nearly 550 sugar mills, with each mill employing 1,000 workers and sourcing cane from nearly 15,000 farmers on average. In this setting, sugar mills therefore become

[11] For details, see https://www.pib.gov.in/FactsheetDetails.aspx?Id=150971

[12] This figure uses data from the Indian Agriculture Census 2015-16.

the primary processing intermediaries that cane farmers transact with[13]. Within mills, cane is crushed to extract juice, and processed into raw or refined sugar. The sugar is then sold to wholesalers and retailers who supply the consumer market.

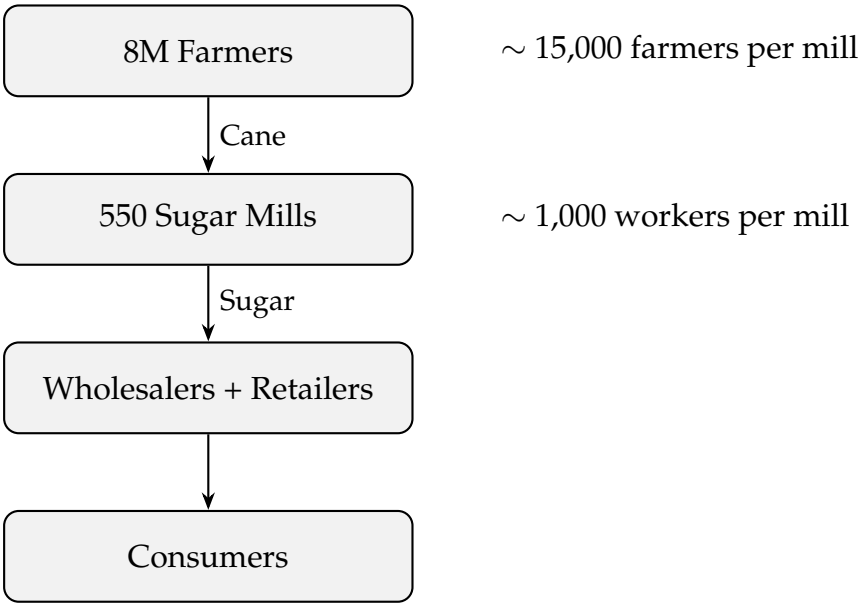



**Figure 2:** The Indian Sugar Value Chain

Mill ownership takes two primary forms: cooperatives and private enterprises. Cooperatives, which are particularly prevalent in Maharashtra and Karnataka, are nominally owned by their farmer-members but managed by elected boards. A natural concern is that cooperatives may face different optimization objectives than private mills, for instance, maximizing member welfare rather than profits (Hansmann, 2000). However, farmer-level data from Maharashtra in Figure A.1 reveals that less than a quarter of cane suppliers to a typical cooperative are registered member-farmers; the remaining three-fourths are non-member suppliers with no ownership stake. Since cooperatives must offer competitive cane prices to attract this large non-member majority who face the same outside options as farmers supplying to private mills, the pricing behaviour of cooperatives in the cane market is likely to resemble that of profit-maximizing private mills. As such, the model that I develop in Section 6 treats ownership status as an observable characteristic entering farmer mill-choice but does not endogenize the governance structure.

## 2.2 Cane Quality Management

A defining feature of the Indian sugar industry is that it is the mill, and not the individual farmer, that designs and coordinates the harvesting schedule during the crushing

[13]Over 80% of all cane produced is utilized for sugar production, with the rest sold to small jaggery producing units or used for self-consumption. I introduce these as an outside option in the inner nest of my nested discrete choice farmer supply model in Section 6.

season, which typically runs for five months from November to April. Mills determine which fields are cut on which days to coordinate the movement of cane from field to factory. This arrangement is common across agro-processing crops whose quality degrades rapidly after cutting — tea, cotton, and cane alike. In such settings, the processor centralizes harvest logistics which helps ensure that the raw material is processed soon after harvest. The stakes are particularly high for cane because its sugar content is time-sensitive at both ends: cane accumulates sucrose as it matures, and begins to lose it through inversion once cut. The two levers that the mill controls – the *maturity* of the cane it schedules for harvest and the *time gap between cutting and crushing* – therefore directly shape how much sugar is ultimately extracted.

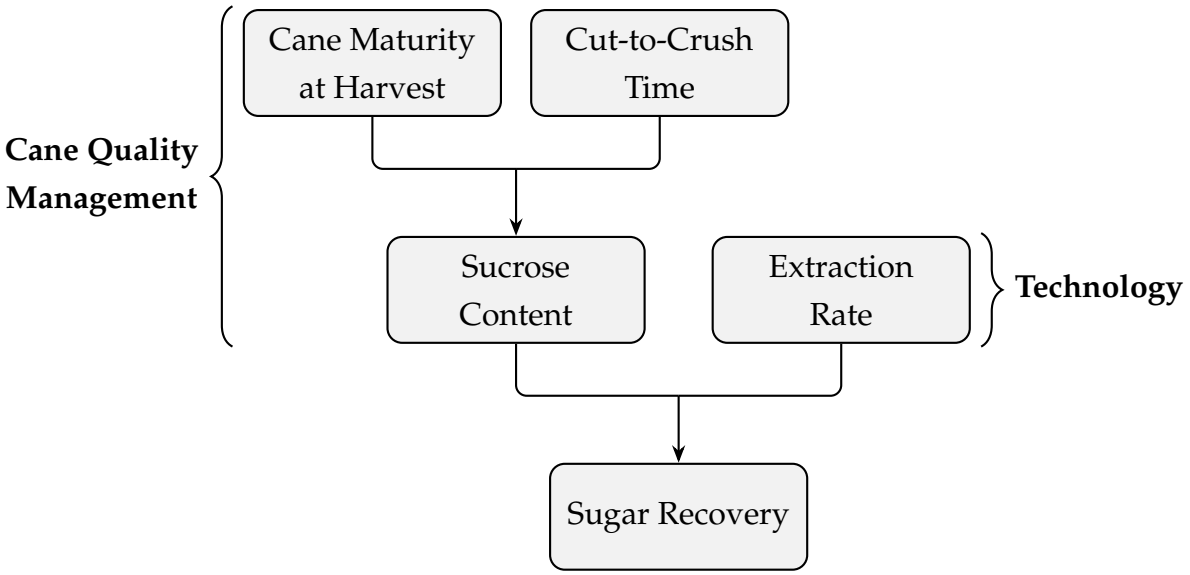
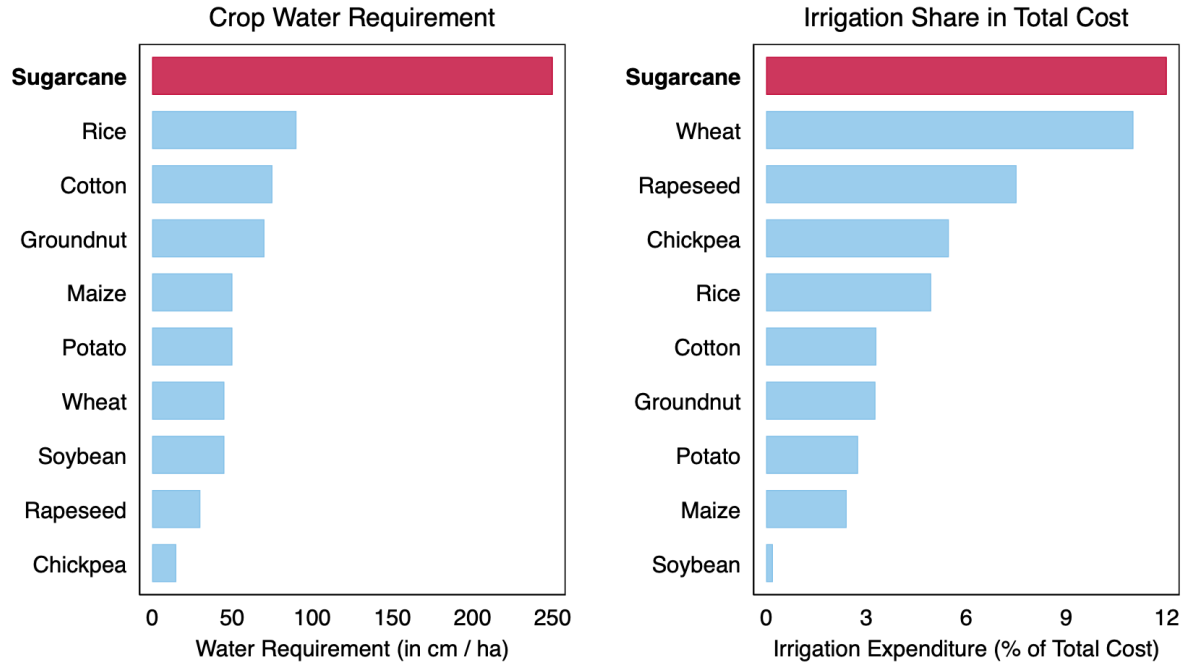



**Figure 3:** Determinants of Sugar Recovery

These harvest decisions are summarized by *sugar recovery*, the share of sugar extracted per unit of cane crushed, which serves as an observable measure of mill productivity in my event studies. Figure 3 illustrates how the operational levers in the mill's control map into recovery: scheduling cane harvest at higher maturity and shortening cut-to-crush intervals raises its sucrose content. Combining these process management practices with sucrose extraction pins down sugar recovery. Because each of these components is reported mill-by-mill and season-by-season in administrative records, it provides a direct, high-frequency window into how effectively each mill manages its harvest — and a productivity margin that, as I show later, responds to the competitive and climatic pressures at the heart of this paper.

## 2.3 Water Intensity and Sensitivity to Droughts




**Panel A:** Crop Water Requirement **Panel B:** Irrigation Share in Total Cost

**Figure 4:** Cane's water intensity makes sugar mills vulnerable to droughts

*Notes:* Panel A shows crop water requirement over the growing season for 10 major crops, while Panel B shows their share of cultivation cost spent on irrigation. *Source:* Indian National Bank for Agriculture and Rural Development (NABARD), and the Cost of Cultivation Surveys.

The Indian sugar industry's vulnerability to droughts stems from the extraordinary water intensity of cane cultivation. Cane requires approximately 250 centimetres of water per hectare over its 12 month growing cycle (Figure 4, Panel A), making it the most water-demanding crop in Indian agriculture. For comparison, sugarcane's water requirement is nearly thrice that of rice, the next most water-intensive major crop. Cane also stands out in terms of expenditure incurred on irrigation, with 12% of its total cost of cultivation spent on irrigation through mainly groundwater, but also canals (Panel B).[14] This is despite the fact that a sizeable part of its growing cycle overlaps with the monsoon season. Crucially, the water intensity extends beyond cultivation into the processing stage. Sugar mills, on average, require 20 cubic metres of water to produce one metric tonne of sugar (Figure A.2). Both the upstream cultivation and downstream processing stages of the supply chain are thus acutely dependent on water, making the entire industry highly sensitive to droughts. This sensitivity is not merely theoretical – it is a recurring feature of India's economic landscape that regularly makes national headlines as can be seen in Figure A.3.

[14] See Banerji, Meenakshi and Khanna (2012); Khanna (2007); Shrivastava, Srivastava and Solomon (2011)

# 3 Data

Studying how droughts reshape market structure, and how that restructuring is distributed between mills and farmers, requires observing both sides of the cane market over a horizon long enough to capture exit and reallocation. On the mill side, I need to follow the universe of sugar mill intermediaries through droughts and after: their operating status and exit, the cane they procure and the sugar they produce, the prices they pay farmers, and — crucially — direct measures of the two margins through which they might respond, namely their processing technology and cane quality management. On the farmer side, I need to observe where farmers sell, how that choice reallocates when a nearby mill exits, and how the prices, yields, and acreage underlying their cane income move in response. Linking the two requires knowing which farmers are exposed to which mills, so that changes in local market structure can be mapped to the farmers who bear them.

**Table 1:** Summary of Main Data Sources

| Variables | Source | Timeline |
|---|---|---|
| **Panel A. Market Level Data** | | |
| District crop output, area, yield, prices | ICRISAT, APY | 1990–2024 |
| Potential crop yields, land-suitability | FAO-GAEZ | Baseline |
| Block crop area, irrigated area, holdings | Agriculture Census | 2000–2020 |
| Village wells & canals coverage | Minor Irrigation Census | 1992–2018 |
| Village groundwater depth | Central Ground Water Board (CGWB) | 1994–2024 |
| **Panel B. Mill Level Data** | | |
| Production, management, technology | Directorate of Sugar, Maharashtra & Uttar Pradesh State Departments | 1990–2025 |
| Cane varieties & agronomic attributes | Directorate of Sugar, AICRP, ICAR-ISRI | 1990–2025 |
| Cane price, labour & wages, capital | Annual Survey of Industries, Maharashtra Sugar Commissionerate | 1993–2023 |
| Entry & expansion costs, licences | Maharashtra Sugar Commissionerate | 1990–2025 |
| Drought adaptation, farmer relations | Online mill survey (Maharashtra) | 2025-2026 |
| **Panel C. Farmer Level Data** | | |
| Cane price, yield, acreage, input use | Cost of Cultivation Surveys (CCS) | 2000–2019 |
| Farmer–mill cane transactions | Maharashtra Sugar Commissionerate | 2020–2025 |
| **Panel D. Droughts** | | |
| SPEI-12 (Drought Index) | Drought Atlas (Chuphal et al., 2024) | 1990–2025 |

I assemble several datasets that jointly capture mill-level operational and financial outcomes, farmer supply behaviour, and drought shocks at a resolution fine enough to identify causal effects within local cane markets. Table 1 summarizes the main variables, their sources, and the period over which each is available. Three novel data contributions underpin the analysis. First, I digitize archival plant-level records from the Indian Directorate of Sugar — the closest available census of the Indian sugar

manufacturing sector — covering the universe of sugar mills from 1990 to 2025 and yielding a panel of unprecedented length and coverage. Second, I obtain first-time access to the complete universe of farmer–mill cane transaction records maintained by the Maharashtra State Sugar Commissionerate, providing georeferenced data on approximately 3 million unique cane farmers. Third, I develop a matching algorithm that links the Directorate's plant-level records to the Annual Survey of Industries (ASI), enabling mill-level price and financial analysis for the first time in the Indian sugar industry literature. The remainder of this section describes the mill-level data (Section 3.1), the drought measures (Section 3.2), and other miscellaneous data (Section 3.3) in turn.

## 3.1 Sugar Mill Level Data

The mill-level data combine four sources: a digitized manufacturing panel, a matched financial panel, an online survey of mill management, and farmer–mill transactions.

### 3.1.1 Manufacturing Data

The core of the database is a mill-year panel constructed from the manufacturing archives of the Indian Directorate of Sugar. These archives constitute the closest available census of the Indian sugar manufacturing sector, covering all registered and operational mills in every crushing season. Through an institutional relationship with the Directorate, I obtain and digitize records spanning 1934 to 2025, although I restrict attention to 1990 to 2025 for this paper. I supplement these with plant-level records from Maharashtra and Uttar Pradesh, India's two largest producing states, which together account for over 70% of national sugar output. Records obtained from the respective state sugar departments provide an independent cross-check on coverage. The final sample comprises 886 firms across 750 mill locations in 20 states.

For each mill-year, the panel records administrative and manufacturing data at each step of the production process: cane procured, sugar produced, time accounting, capacity utilization, management, technology, and productivity. Sugar recovery — the amount of sugar produced per unit of cane crushed — is an observable measure of mill-level productivity. Recovery is the product of two conceptually distinct stages that the data let me measure separately: the *sucrose content* of the cane reaching the mill gate, reflecting cane variety, harvest timing, and the cut-to-crush interval; and the *extraction efficiency* with which the factory converts that sucrose into sugar, reflecting processing technology. This split between field-level cane management versus factory-level technology is the central measurement for the paper's mechanism, since it distinguishes recovery gains originating in cane quality from those requiring technological investment. Operational status is coded as working, suspended, or exited, with permanent exit assigned when a

mill is not working for more than three years with no subsequent resumption, or when records confirm acquisition or liquidation.

The panel also records the cane varieties procured by each mill in each season, providing a direct measure of varietal composition over time. I link these variety names to agronomic attributes — potential sucrose content, yield, maturity class, and agro-climatic zone — using variety-performance data from the All India Coordinated Research Project (AICRP) on Sugarcane, and Vasantdada Sugar Institute's (VSI) variety-evaluation database. I obtain drought- and stress-tolerance classifications from the ICAR-Indian Sugarcane Research Institute. Together these allow me to construct an annual mill-level cane-variety index for each sugar mill.

### 3.1.2 Financial Data

Cane input prices and financial data at the mill level are drawn primarily from the Annual Survey of Industries (ASI), conducted by India's Ministry of Statistics and Programme Implementation. The ASI covers all factories registered under the Factories Act, 1948, and reports revenues, costs, wages, capital, material inputs, and output. It is the principal source of industrial statistics in India and the only source providing a standardized, all-India financial panel for manufacturing plants. A central challenge is that the ASI does not identify factories by name: it uses an internal factory code, not publicly linked to plant identities, that changes with ownership transfers or re-registration. I overcome this through a matching algorithm that exploits variables common to the archival plant records and the ASI, yielding a matched panel for the near-universe of sugar mills over 1993–2023 and enabling mill-level cane-price and financial analysis for the first time in this literature.

For Maharashtra, three additional sources enrich the financial data. First, the Sugar Commissionerate publishes mill-level price reports recording the cane price paid to farmers by season. Second, the Vasantdada Sugar Institute maintains detailed cost-of-production records for sugar mills in Maharashtra from 1998 to 2025, which serve both as an independent validation layer for ASI derived cost variables and as a primary source for mills outside the ASI match. Third, I draw on mill and capacity expansion licences maintained by the Commissionerate from 1990–2025, which document the year of application, the year of first crushing/expansion, and directly observed costs decomposed into land, machinery, and building costs. This is, to my knowledge, the only source of directly observed entry and expansion costs for Indian sugar mills.

### 3.1.3 Online Mill Survey

To supplement the administrative records with information on management practices and organizational structure not captured in the panel, I conduct an online survey of

220 sugar mills in Maharashtra, circulated through the Sugar Commissionerate. The survey covers drought risk and adaptation, harvest-scheduling practices, extension-staff deployment, seed-distribution programmes, and recent capital investments — the management inputs that the model identifies as the channel for within-firm productivity upgrading.

#### 3.1.4 Farmer–Mill Transactions

Under Maharashtra's mandatory cane-registration system, the Sugar Commissionerate maintains a complete record of every farmer–mill cane transaction in the state. For each crushing season from 2020 to 2025, the records document, for every farmer supplying cane to every mill, the farmer's village, cane variety grown, area under cane, maturity class, and cooperative-membership status. I georeference these records by matching Commissionerate village names to census village identifiers through a multi-stage fuzzy-matching pipeline. The final output covers approximately 3 million unique farmers across more than 220 mills and 16,000 villages, and provides the choice-set variation that identifies farmers' mill-selection behaviour.

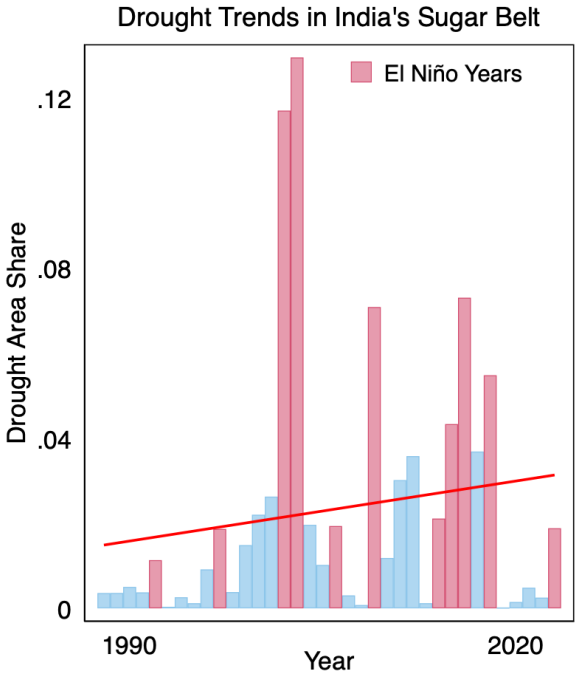
### 3.2 Droughts

The treatment variable throughout the main analysis is an indicator for an extreme drought in a local market, constructed from the Drought Atlas of India (Chuphal et al., 2024), a high-resolution dataset providing monthly Standardized Precipitation Evapotranspiration Index (SPEI) values across India from 1901 to 2025. Unlike precipitation-only measures such as the SPI, the SPEI captures water demand as well as supply: it nets temperature-driven evapotranspiration against rainfall, and so reflects the crop-water stress that matters for a thirsty crop like sugarcane.The SPEI values are constructed using the Hargreaves method, which requires only minimum and maximum temperature and extraterrestrial radiation as inputs, and is considered highly reliable for Indian climatic conditions. I use the 12-month accumulated SPEI measured over January to December, chosen to match the sugarcane cultivation cycle. Cane is typically planted early in the calendar year and harvested at its close, so a January-to-December window captures the full annual water balance relevant to the standing crop. I classify a district-year to be hit by an extreme drought when the index falls to $-2$ or below, which corresponds approximately to a 1-in-50-year event, in more than 10 percent of the district's cane catchment.

Construction proceeds in three steps. First, I aggregate the Drought Atlas's native resolution data to the full cane catchment within each district. Second, I classify a market as drought-hit in a given year if more than 10 percent of this area records SPEI $\leq -2$. I adopt an area-share threshold so that the indicator reflects a market-wide shock

to cane supply. This is appropriate because mills draw cane from catchment areas of roughly 50 kilometres, so a drought covering a tenth of the district's cane catchment affects procurement across most of its mills. I take the district as the relevant market throughout, consistent with the local nature of cane trade documented in Section 5.2. Third, because a district may experience several droughts over the three-decade sample, I retain only its single most severe event, defined as the year in which the largest share of the district's area falls below SPEI $\leq -2$.[15] Keeping the drought of broadest spatial coverage assigns each treated district one cleanly defined treatment year, which the staggered event-study design in Equation 1 requires.

**Figure 5:** Extreme drought coverage has doubled across India between 1990-2025



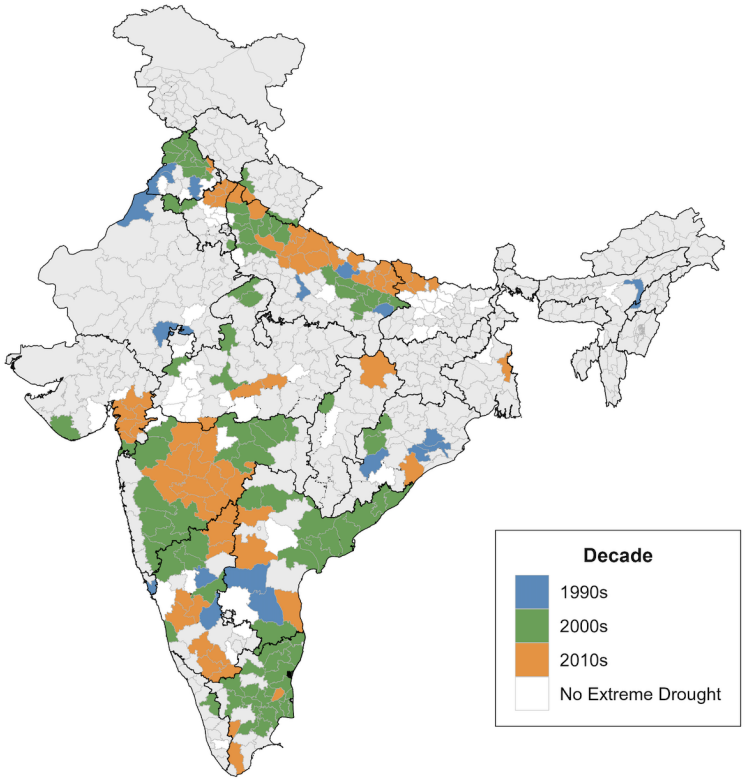

These SPEI-based droughts correspond to genuine agro-climatic shocks. In a treated drought year, a district experiences, on average, around six additional degree-days above 30°C and a 20 percent decline in precipitation relative to its own norm, confirming that the index is picking up episodes of combined heat and water stress rather than statistical noise (Figure A.4). Consistent with their climatic origin, the identified droughts also cluster disproportionately in El Niño years as shown in Figure 5, linking the local shocks I exploit to the large-scale climate variability whose extremes are projected to intensify under warming. As Figure A.5 shows, India sits squarely in El Niño's zone of influence, exposed to warm and dry conditions during the winter and monsoon respectively.

Over the sample period, this procedure yields 170 treated districts across 20 cane producing states, each contributing a single most-severe drought year, with treatment

[15] A third of treated districts experience multiple extreme droughts over the sample period; the remainder experience a single or no drought episode. See Table B.2 and Figure A.6 for more details.

timing staggered across 20 distinct years. Figure 6 maps this incidence, colour-coding each district by the decade of its most severe event. The map reveals rich variation across space and time. Treated districts span every major sugar-producing region, with no single state or decade bearing the shock exclusively.

**Figure 6:** Drought Incidence across Sugar Producing Districts




## 3.3 Market and Farmer Level Data

I complement the core datasets with agricultural, irrigation, and geographic sources that enter as controls, as inputs to the farmer supply model, and in robustness checks. District-level crop output, acreage, yields, and prices for the major crops entering the Fréchet outer nest come from the ICRISAT District-Level Database through 2017, extended with Area, Production, and Yield (APY) statistics from the Directorate of Economics and Statistics thereafter. FAO-GAEZ potential crop yields under local agro-climatic conditions are used to construct land-suitability parameters. The quinquennial Agriculture Census (2000-2020) provides block- and district-level crop and irrigated area, and the Minor Irrigation Census rounds (1992-2018) record dependence on tubewells and canals for irrigation. Finally, observation-well groundwater-depth measurements from the Central Ground Water Board (CGWB) enter both the event study and as a control for irrigation dependence. The Cost of Cultivation Surveys (2000-2019) additionally supply input costs, revenues, and yields for the major crops used in the supply model.

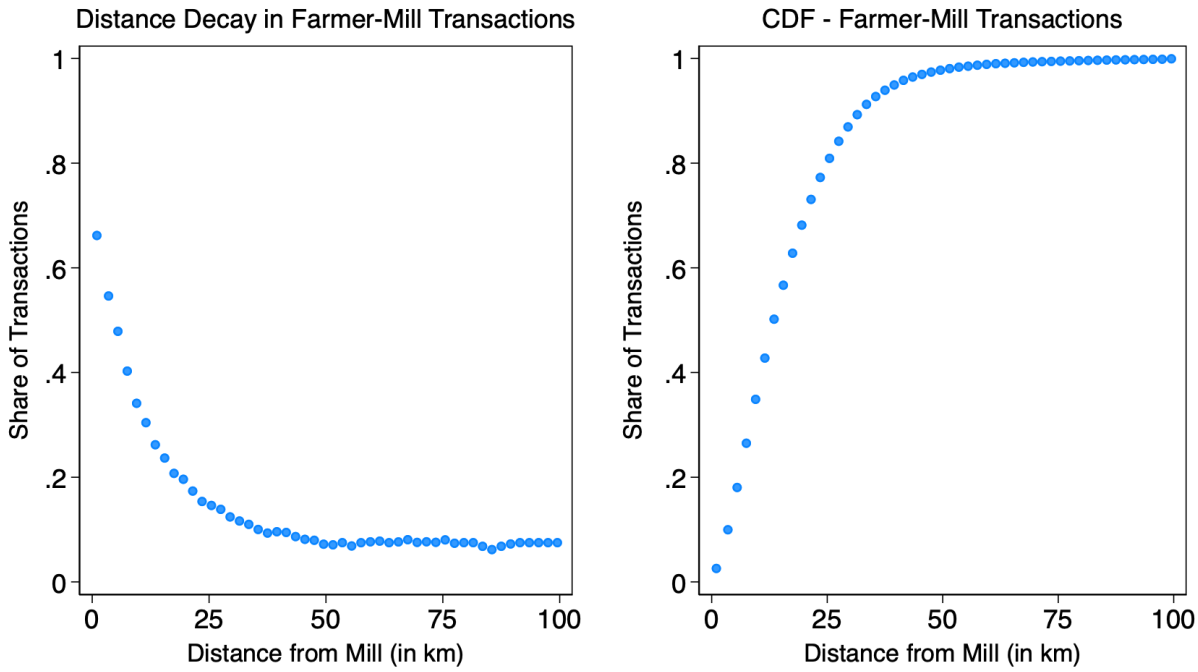
# 4 Stylized Facts

Before turning to the event study results, I present three stylized facts that establish the institutional conditions under which the paper's mechanism operates.

**Fact 1: Trade in cane is highly localized, generating spatially segmented markets.**

Cane markets are spatially segmented to a degree that is unusual even among agricultural commodities. Using georeferenced farmer-mill transaction data, I document extreme distance decay in farmer-mill relationships. Figure 7, panel A plots the share of farmers selling to a given mill as a function of the distance between them. Among farmers located within 5 kilometres of their closest mill, 70 percent sell their cane to that mill, and this share drops to less than 10 percent by 50 kilometres. Figure 7, panel B presents the cumulative distribution function: roughly 80 percent of all farmer-mill transactions take place within 25 kilometres of a mill and virtually all trade in cane exhausts within 50 kilometres of a mill.

**Figure 7:** Trade in cane exhausts within 50 kms of a mill



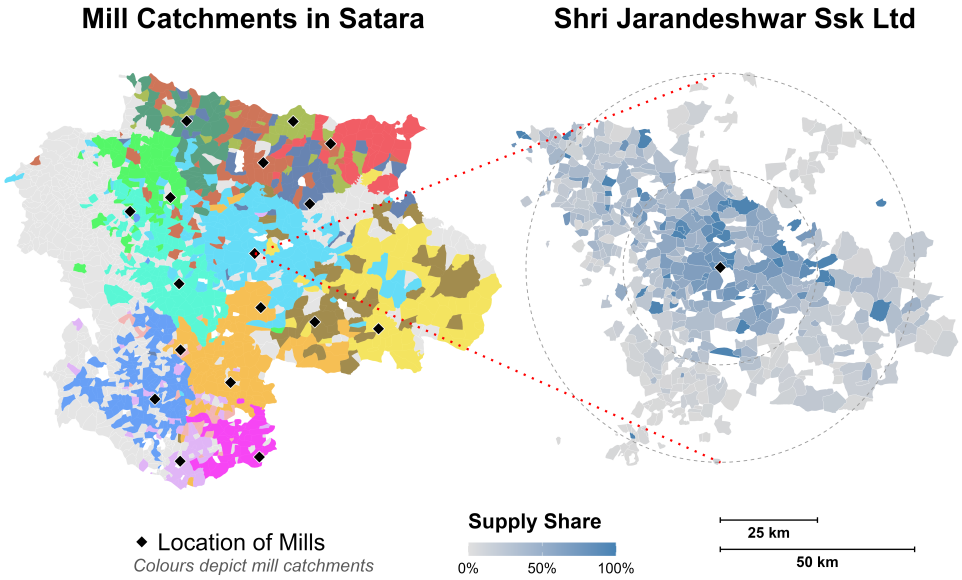

**Panel A:** Distance Decay **Panel B:** CDF - Distance Decay

*Notes:* Panel A shows the share of farmers selling to a given mill as a function of the distance between them. Panel B plots the CDF. *Source:* Farmer-Mill Transactions from the Maharashtra Sugar Commissionerate.

This extreme spatial concentration arises from the rapid post-harvest deterioration of sugar content in cane. Once cut, cane loses recoverable sugars rapidly due to

microbial activity and chemical inversion of sucrose into non-recoverable reducing sugars – glucose and fructose. This perishability creates strong incentives for mills to source cane from nearby farms and crush cane within 12-18 hours of harvesting. Such a highly localized nature of trade in cane gives rise to spatially segmented markets as illustrated in Figure 8. Panel A maps the district of Satara in Maharashtra, with each village colour-coded by the mill that receives the largest share of its cane and reveals sharp spatial partitioning. Panel B zooms into the catchment area of a single mill, showing that the mill's procurement share across surrounding villages decays steeply with distance – consistent with the distance gradient documented in Figure 7.

**Figure 8:** Cane markets are spatially segmented



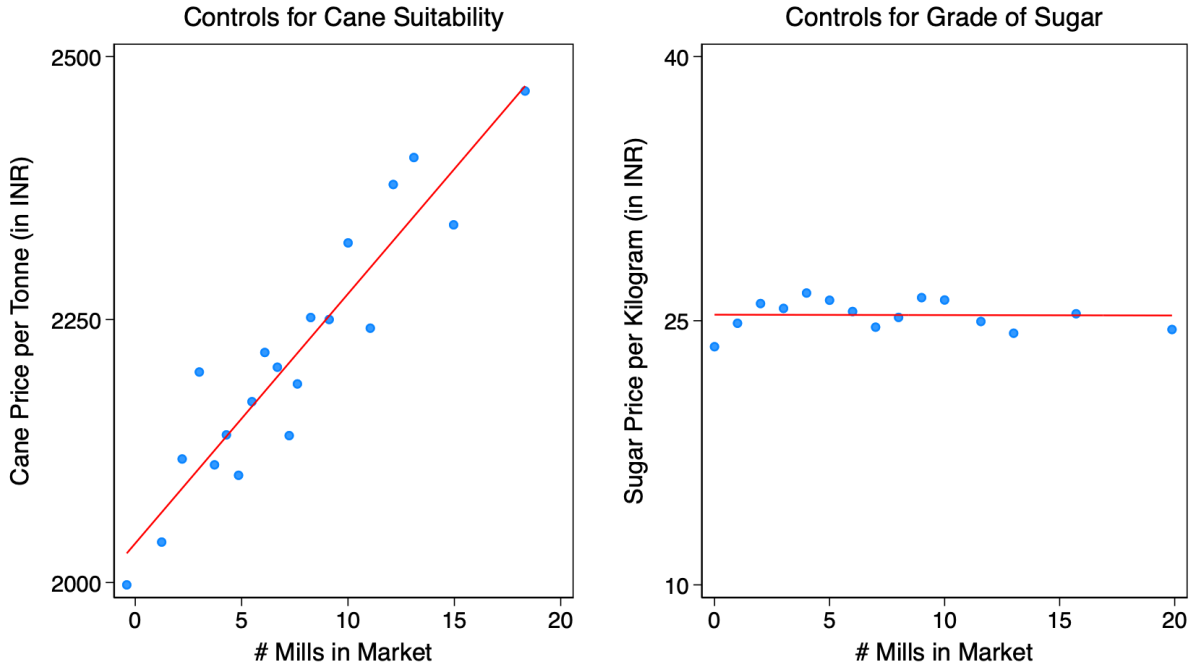

*Notes:* The plot on the left shows the distribution of mill catchments in the district of Satara, Maharashtra. The plot on the right zooms into the catchment for one mill, showing the mill's procurement share across supplying villages in a 50 km radius. *Source:* Farmer-Mill Transactions from the Maharashtra Sugar Commissionerate.

This fact has three implications for the paper. First, it defines the relevant market: cane markets are local, and market concentration measures defined at the district level capture meaningful variation in competitive conditions. I therefore adopt the district as the unit of a local market throughout the analysis. This choice is validated by farmer-mill transaction data from Maharashtra, which shows that cross-district trade in cane accounts for only 10 percent of all transactions (Figure A.7) – the vast majority of cane procurement occurs within district boundaries. Second, it ensures that when a mill exits, its farmers are reallocated to nearby surviving mills. Third, it creates oligopsony power: with only a fixed set of mills within farmers' economical transport distance, each mill faces a local supply curve with limited elasticity, giving it price-setting power over cane procurement.

**Fact 2: Mills set cane prices, but are price-takers in sugar markets.**

Cane markets are spatially segmented because cane is bulky, perishable, and costly to transport. This feature creates local oligopsonies: a given farmer's choice set is limited to the few mills within economical transport distance. To protect farmers, cane prices are subject to regulatory price floors in the form of a centrally determined Fair and Remunerative Price (FRP) and, in several states, the higher State Advised Price (SAP).[16] However, these floors are not binding in practice: more than 90% of all observations in the data see farm-gate cane prices above the price floor. Panel A of Figure 9 demonstrates the resulting oligopsony power: cane prices paid to farmers are higher in markets with a greater number of mills, after controlling for cane quality and suitability. Moving from near-monopsony to a competitive market of 15 mills raises cane prices by approximately 25 percent, suggesting price-setting power by mills in cane markets.

**Figure 9:** Mills have price-setting power in cane markets




**Panel A:** Cane Prices **Panel B:** Sugar Prices

*Notes:* Panel A shows a binscatter plot for farm-gate cane prices against local market structure after adjusting for cane quality and suitability. Panel B shows a binscatter plot for ex-mill sugar prices against local market structure after adjusting for the grade of sugar produced. Data is for year 2010. *Source:* Plant-level Records from the Indian Directorate of Sugar and the ASI.

[16]Four states - Uttar Pradesh, Punjab, Haryana and Uttarakhand set their own State Advised Price (SAP), which specifies two to three distinct prices according to the cane variety a farmer grows; the remaining states follow the centrally determined Fair and Remunerative Price (FRP), which combines a baseline price with a premium that increases in the mill's sugar recovery. The FRP schedule for the year 2018 can be seen in Figure A.9

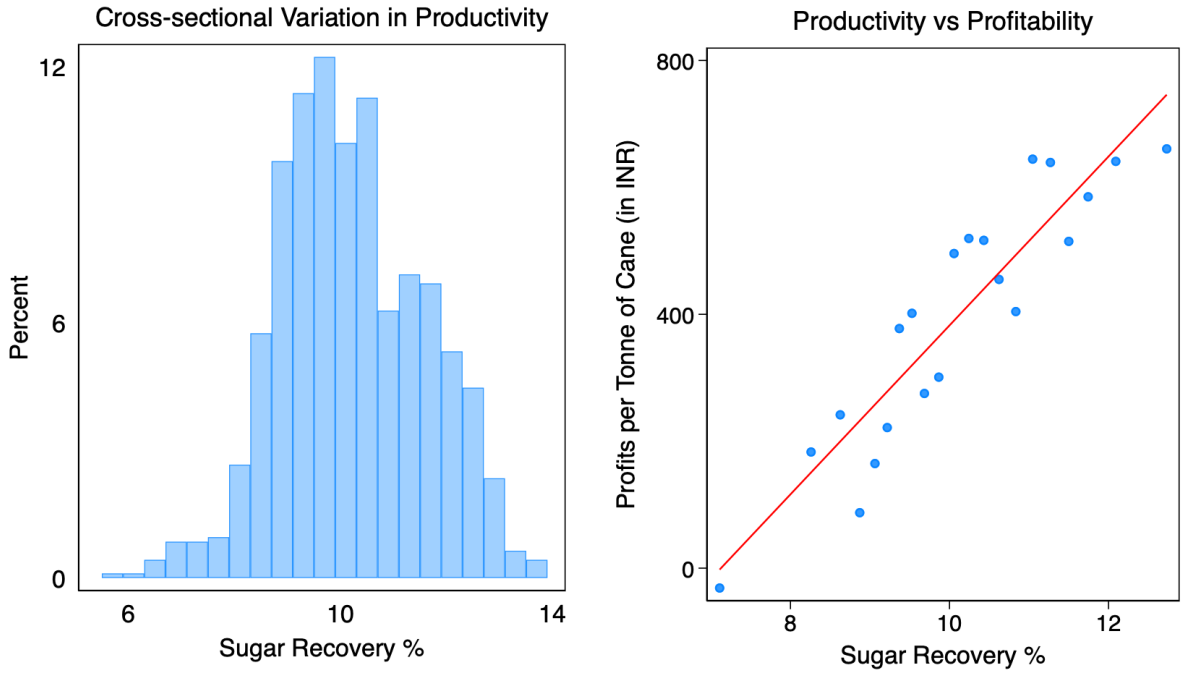
On the output side however, the picture is starkly different. Sugar prices are effectively determined by government regulation through a system of monthly release quotas that control how much sugar each mill can sell in a given month. An example of such a monthly sugar release allocation can be seen in Figure A.8 for sugar mills in Punjab. Since each mill's saleable quantity is administratively fixed, no individual mill can influence the market price by expanding or withholding supply. Panel B of Figure 9 confirms this: ex-mill sugar prices in the year 2010 show no systematic relationship with local market structure after controlling for the grade of sugar produced. Sugar prices are seen hovering around Rs. 25-26 per kilogram regardless of how competitive a mill's local market is, as measured by the number of mills located in the district. Market power, absent on the output side but pronounced on the input side, is a defining feature of the industry and motivates the oligopsony model I develop in Section 6.

**Fact 3: Mills vary widely in productivity, and the least productive operate on the thinnest margins.**

I use sugar recovery as an observable measure of mill productivity and find that mills differ enormously in how efficiently they convert cane into sugar. Figure 10, panel A plots the distribution of sugar recovery across mills and reveals substantial cross-sectional dispersion. Recovery ranges from roughly 6 to 14 percent, implying that the least productive mills extract less than half as much sugar per tonne of cane as the most productive. Because sugar revenue is linear in recovery, differences of this magnitude translate into large differences in the value a mill generates from the same quantity of cane. This productivity dispersion maps directly into profitability. Panel B plots profit per tonne of cane against sugar recovery, and shows a strong positive gradient. The least productive mills operate on the thinnest margins, while high-recovery mills earn substantially more per tonne crushed. The relationship is intuitive – a low-recovery mill extracts less sugar from each tonne of cane it purchases, yet pays a cane price anchored by the regulated floor and by competition for cane as described in Fact 2, so its margin is compressed from both sides. Low recovery is therefore not merely a technical inefficiency, it is a direct determinant of financial fragility.

This fragility is what makes productivity dispersion consequential for how the industry responds to drought shocks. Droughts sharply contract cane availability for up to two years after the drought itself. When cane becomes scarce, every mill faces lower throughput, but thin-margin mills have the least buffer to absorb a prolonged period of underutilized crushing capacity. The least productive mills are thus the most exposed to drought. Already operating close to the break-even point, they are the first to become unviable when a shock decimates local cane supply.

**Figure 10:** Mills differ in productivity, with laggards facing thinner margins




**Panel A:** Sugar Recovery

**Panel B:** Profits

*Notes:* Panel A shows a cross-sectional histogram on sugar recovery. Panel B shows a binscatter plot for sugar recovery against profits per tonne of cane. *Source:* Plant-level Records from the Indian Directorate of Sugar and the Annual Survey of Industries.

Taken together, the three facts establish the conditions for the paper's mechanism. **Fact 3** identifies which mills are at the margin of survival, and hence which mills a drought is likely to force into exit – a selection that is central to the restructuring mechanism I study. **Fact 1** implies that drought-induced reallocation is not random across space: it removes the least productive mills and reallocates their cane to local survivors, reshaping local market structure and, through the oligopsony power documented in **Fact 2**, the prices farmers ultimately receive. This selection-and-reallocation mechanism is the focus of the model developed in Section 6. The next section presents the event study evidence that these ingredients produce.

# 5 Empirics

## 5.1 Empirical Strategy

My identification strategy exploits spatial and temporal variation in the incidence of extreme drought events across India's sugar-producing districts. Extreme droughts are defined as district-year observations where the Standardized Precipitation Evapotranspiration Index (SPEI) falls below -2 for at least 10 percent of the district area as

defined in Section 3, corresponding to a 1-in-50 year event. Because sugar production is geographically dispersed across India, different districts experience extreme droughts at different times, providing quasi-experimental variation in the external shock. To analyze the effects of these drought shocks, I implement an event-study design at two levels:

At the **market level**, I use the following specification:

$$y_{dt} = \sum_{k=\underline{T}}^{\bar{T}} \beta_k D_{dt}^k + \delta_d + \lambda_{zt} + \varepsilon_{dt} \tag{1}$$

where $y_{dt}$ is the outcome for district $d$ in year $t$, $\delta_d$ are district fixed effects absorbing time-invariant market characteristics, $\lambda_{zt}$ are cane climatic zone-year fixed effects absorbing common annual shocks within cane zones, and $D_{dt}^k$ are event-time indicators defined relative to the year in which district d experiences its worst extreme drought.

At the **plant level**, I use the following specification:

$$y_{it} = \sum_{k=\underline{T}}^{\bar{T}} \theta_k D_{it}^k + \delta_i + \lambda_{zt} + u_{it} \tag{2}$$

where $y_{it}$ is the outcome for mill $i$ in year $t$, $\delta_i$ are mill fixed effects, $\lambda_t$ are cane climatic zone-year fixed effects. Each mill's treatment assignment is based on the drought status of the district in which it is located. The coefficient for the event year ($k = 0$) is normalized to zero. Both specifications contain lags and leads from -8 to +12 years around the event respectively, but I restrict the figures to show treatment effects from -5 to +10.

India comprises four distinct cane climatic zones, shown in Figure A.10. Cane climatic zone-year fixed effects absorb all shocks common to mills sharing an agro-climatic environment in a given year, such as weather and suitability for distinct cane varieties, and help identify drought effects from variation across mills within the same zone and year. Given the staggered implementation of droughts across districts, I estimate all dynamic treatment effects using the Sun and Abraham (2021) estimator, which addresses concerns about bias from heterogeneous treatment effects in staggered difference-in-differences settings. For robustness, I also estimate using standard two-way fixed effects and show that the results are very similar.

The key identifying assumption is that, in the absence of droughts, outcomes for mills (or districts) in affected areas would have followed similar trends as those in unaffected areas, conditional on mill (or district) and zone-year fixed effects. The features supporting identification are: (i) the incidence of extreme drought is plausibly exogenous

to local economic conditions, being driven by large-scale climatic phenomena as described in Section 3; (ii) the spatial variation across districts experiencing drought in different years provides multiple treatment cohorts, with approximately a quarter of the districts never experiencing an extreme drought during the sample period, serving as a permanent control group; and (iii) the pre-treatment event-study coefficients are statistically indistinguishable from zero, supporting the parallel trends assumption.

## 5.2 Markets

First, I look at the market response to extreme droughts. In particular, I investigate the *direct* effects on cane supply, and *indirect* effects on local market structure operating through the supply shock using the event-study specification in Equation 1.

### 5.2.1 Result 1: Cane supply in drought-hit markets contracts for up to 2 years

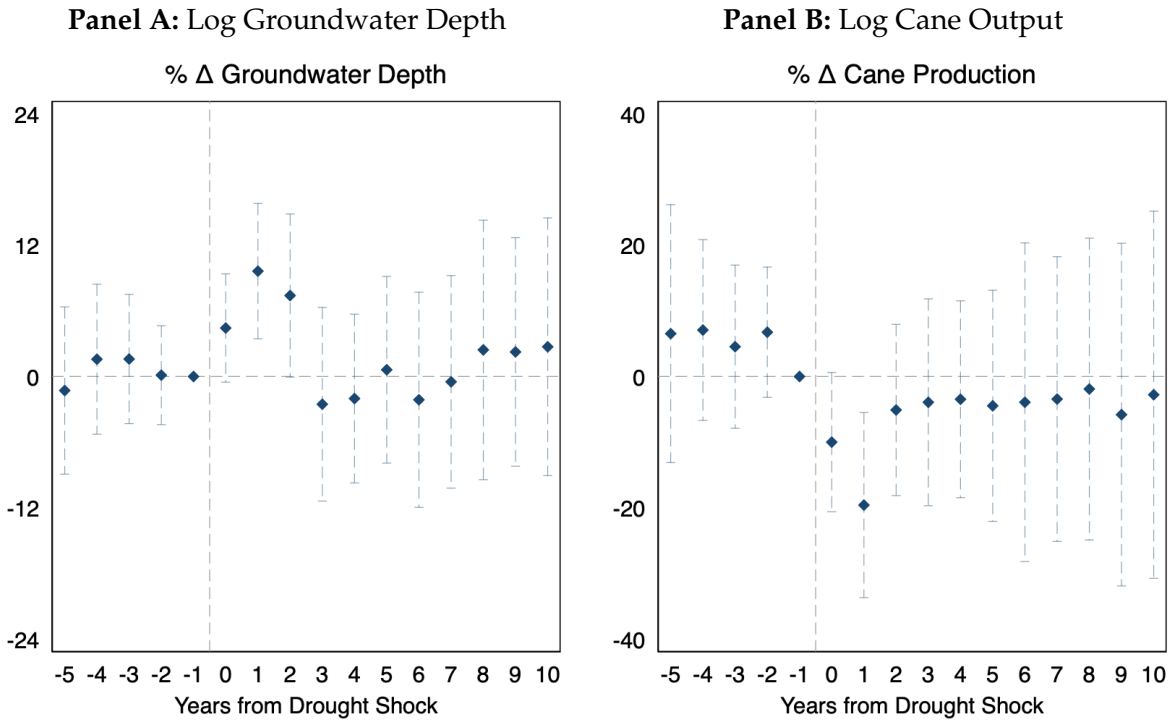



**Figure 11:** Droughts raise groundwater depths and reduce cane output temporarily

*Notes:* Panels A and B present event-study coefficients from Equation 1 using the Sun and Abraham (2021) estimator on annual district-level groundwater depth and cane output data respectively. 95% confidence intervals are computed based on standard errors clustered at the district level. *Source:* Central Groundwater Board (CGWB), ICRISAT and the Indian Directorate of Economics and Statistics.

Droughts have a multi-year effect on cane supply through a hydrological channel. Figure 11 presents event study estimates of the effect of an extreme drought on market-level groundwater depth and cane production. Panel A shows that groundwater depth

increases sharply after a drought by more than 10 percent, and recovers within 2-3 years as aquifers take time to recharge. Given groundwater forms the primary source of irrigation for cane in India[17], this temporary increase in groundwater depth translates into lower cane acreage as can be seen in Figure A.11. Figure 11, Panel B shows the downstream consequence for agriculture: cane production falls significantly by up to 20 percent in affected markets, with the contraction persisting for 2 years before starting to approach pre-drought levels. After the short-term effects of droughts subside, cane production continues to stay approximately 5 percent below pre-drought levels, although this difference is not statistically significant.

These results establish the shock that triggers the mechanism: an extreme drought generates a multi-year contraction in cane supply that reduces low productivity mills' revenues and potentially pushes them below the viability threshold. Crucially, as I document next, while the supply shock is temporary, the exit it causes is permanent. The asymmetry between the speed of agricultural recovery and the irreversibility of industrial exit is what generates the persistent shift in market structure and drives the paper's results.

#### 5.2.2 Result 2: Droughts cause the least productive mills to exit and their farmers to reallocate to nearby survivors

Figure 12, Panel A shows that the number of active mills in a district falls by approximately 10 percent, on average, after a drought in the long-term. The large dip in period 1 reflects the temporary exit of some mills, which re-enter in period 2. Many of these, however, exit permanently over the following three years, and the number of mills in the market stabilizes about five years after the drought, leading to a permanent restructuring of drought-hit markets in the long-term.

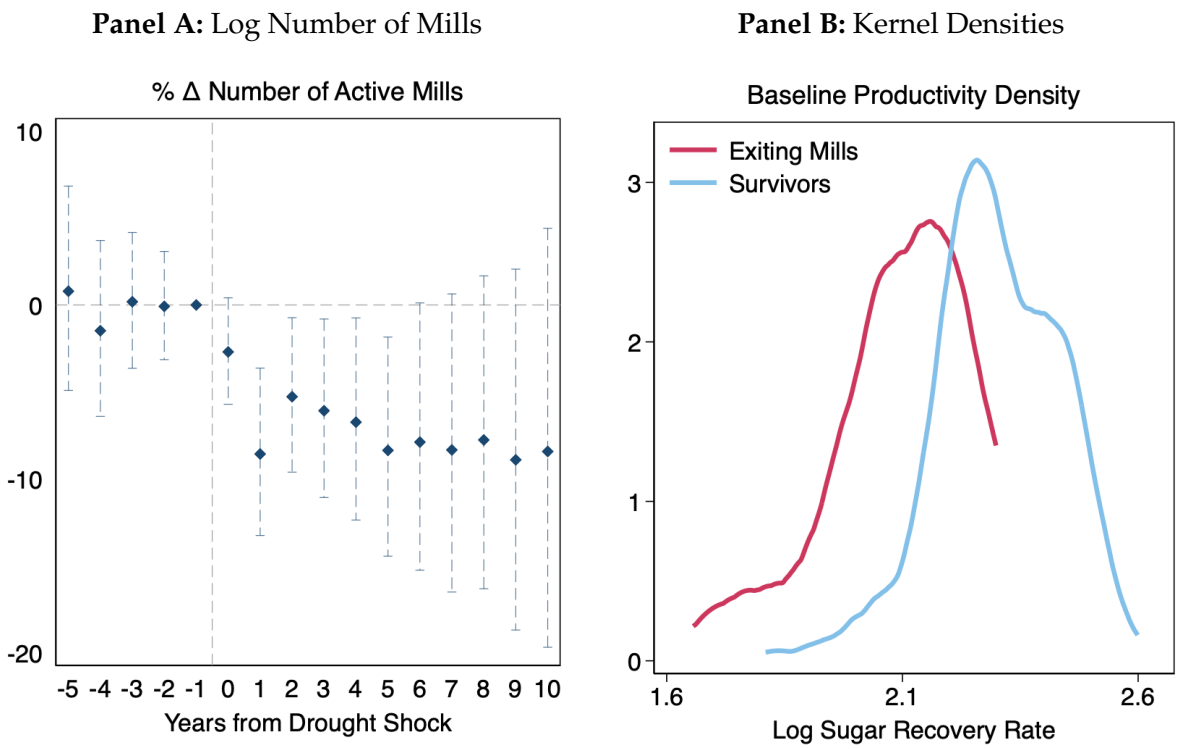
Panel B shows that droughts do not kill mills randomly, they selectively remove the least productive ones. The separate kernel densities of log sugar recovery for surviving and exiting mills in the year before the drought reinforces this finding. Exiting mills are drawn overwhelmingly from the left tail of the productivity distribution at baseline. I examine productivity-based selection on exit in more detail in Table B.1. I find that extreme droughts increase the probability of mill exit by 2.9 percentage points, and mills in the bottom tercile of pre-drought recovery distribution are 3.6 percentage points more likely to exit on top of the baseline effect of 1.8 percentage points for mills in the top two terciles.

Credit-market frictions reinforce this selection. Faced with a severe revenue shock, mills

[17] See Banerji, Meenakshi and Khanna (2012); Khanna (2007); Shrivastava, Srivastava and Solomon (2011)

might in principle borrow to bridge the drought; in practice, they cannot. Appendix Figure A.12 shows no change in outstanding loans for surviving mills in the years following a drought, indicating that credit does not expand to cushion the shock precisely when it is most needed. My online mill survey corroborates this: 70% of mills report finding it extremely difficult to secure credit during droughts. Unable to borrow against the downturn, the least productive mills – already operating on the thinnest margins – are the first to be pushed into exit.

**Figure 12:** Droughts trigger exit of less productive mills

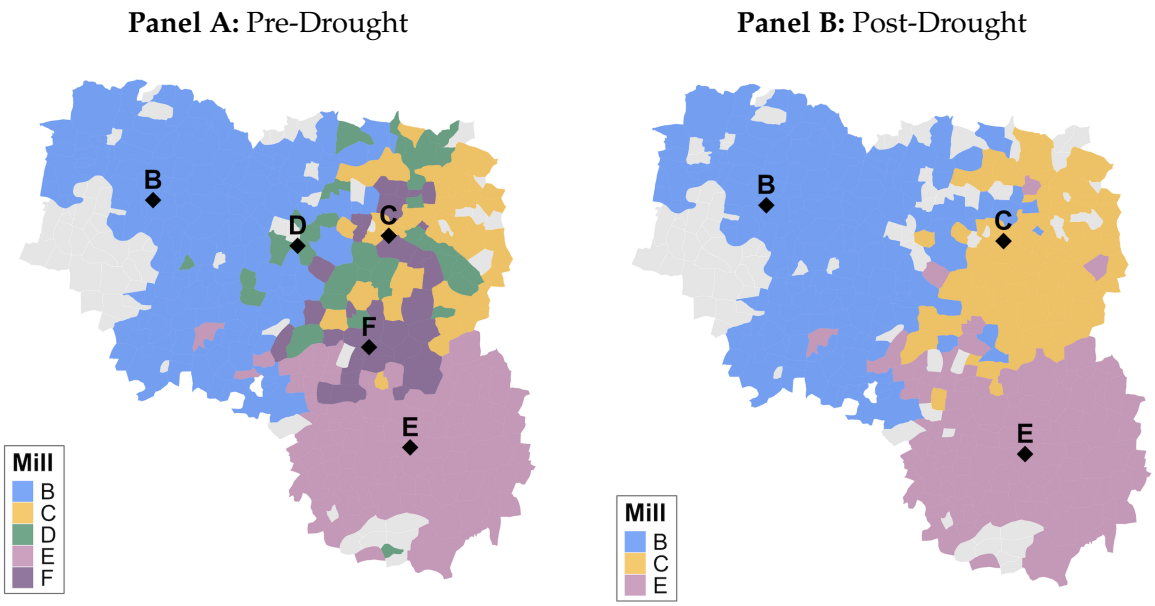



*Notes:* Panel A presents event study coefficients from Equation 1 using the Sun and Abraham (2021) estimator on log number of active mills. Panel B presents the baseline productivity densities for exiting and surviving mills using log sugar recovery as the observable measure of mill productivity. *Source:* Plant-level Records from the Indian Directorate of Sugar.

The return of long-term aggregate cane supply in drought-hit markets to pre-drought levels, as documented in the empirical result in 5.2.1, implies that mill exit drives reallocation of their cane farmers to nearby survivors. Figure 13 provides a vivid illustration from Solapur district in Maharashtra. Panel A maps the pre-drought market structure, with five mills dominating their respective contiguous catchment areas. Panel B shows the post-drought structure: two mills have exited, and their former catchment areas have been absorbed by the three surviving mills, which now control substantially larger spatial footprints. This is the reallocation mechanism in action. Figure A.13 distills these findings into an effect on local market concentration measured through a Herfindahl-Hirschman Index (HHI) using cane procurement and sugar

production shares respectively. Drought-induced exit of unproductive mills and the reallocation of their farmers to survivors together lead to a sharp and persistent increase in concentration.

**Figure 13:** Drought-induced Change in Market Structure in Solapur, Maharashtra




*Notes:* The figure plots changes in market structure induced by exit of anonymized Mills D and F following a drought in northern Solapur in Maharashtra in 2022. *Source:* Plant-level Records from the Indian Directorate of Sugar, and Farmer-Mill Transactions from the Maharashtra Sugar Commissionerate.

## 5.3 Sugar Mills

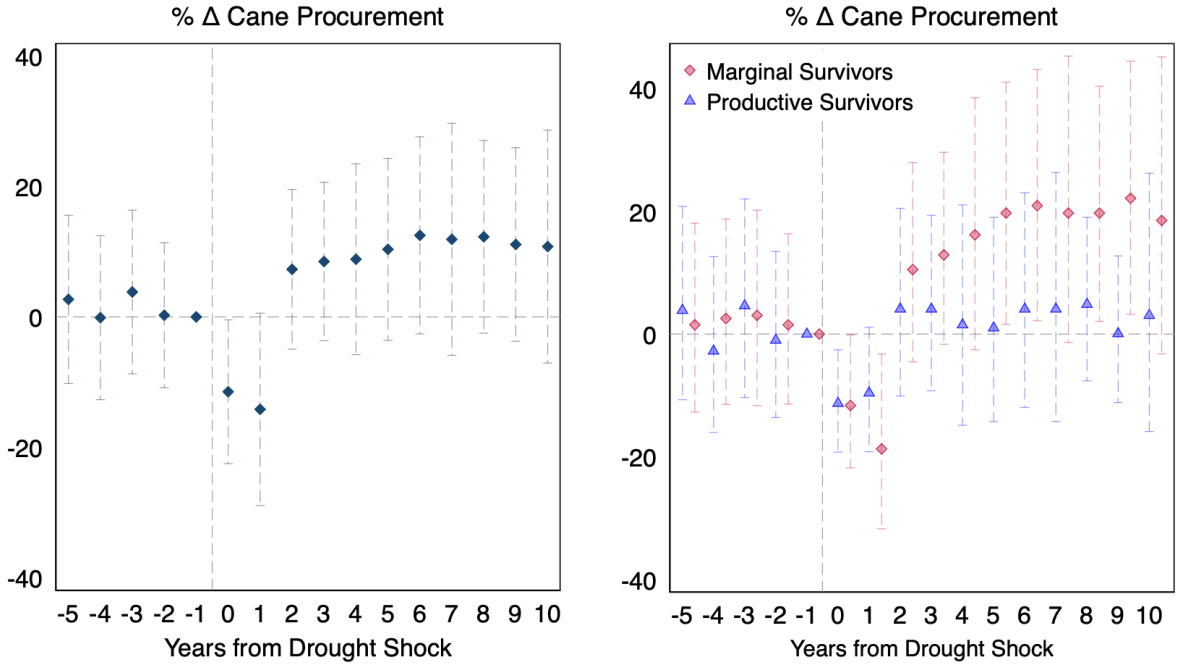
Next, I look at how survivng mills respond to drought-induced market restructuring captured in Section 5.2 using the event-study specification in Equation 2. I start by looking at how reallocated cane flows to survivors, followed by their productivity response, and finally I study impacts on cane prices offered by mills to farmers.

### 5.3.1 Result 3: Cane from exiting mills is reallocated especially to marginal survivors, who are capacity-unconstrained at baseline relative to productive survivors

Figure 14, Panel A presents event-study estimates of the effect of droughts on cane procurement for the full sample of sugar mills. In the short-run, survivors' cane procurement falls by 15-20% reflecting lower output in the aftermath of droughts. Once droughts subside, cane procurement recovers, and rises by more than 10% in the long-term. To understand which types of survivors benefit from mill exit, I break down the sample of surviving mills into two groups – *productive* survivors, and *marginal* survivors. I create the two groups using a median split on average mill-level sugar

recovery in the two years preceding the drought. Productive survivors, therefore, refer to surviving mills that lie in the top-half of the pre-drought sugar recovery distribution, while marginal survivors lie in the bottom-half of the distribution.

**Figure 14:** Reallocated cane flows mainly to capacity-unconstrained, marginal survivors




**Panel A:** Cane Procurement - Full Sample **Panel B:** Cane Procurement - Heterogeneity

*Notes:* Panel A presents event-study coefficients from Equation 2 using the Sun and Abraham (2021) estimator on plant-level cane procurement for the full sample. Panel B breaks the aggregate effect down into separate effects for productive and marginal survivors. 95% confidence intervals are computed based on standard errors clustered at the district level. *Source:* Plant-level Records from the Indian Directorate of Sugar.

Panel B presents event-study estimates of the effect of drought on cane procurement separately for productive and marginal survivors. Marginal survivors see their procurement expand by 20 percent in the years following the drought – a substantial volume windfall. Productive survivors, on the other hand, see a modest increase in their cane procurement. These findings point towards an overwhelming redistribution of cane from exiting mills towards marginal survivors, which is explained by the capacity constraints that productive survivors face as I argue next.

**Capacity constraints.** Table 2 shows that the two groups differ substantially in operational performance. Productive survivors have significantly higher sugar recovery and installed capacity, and they crush more cane compared to marginal survivors. They also employ substantially more workers and pay higher cane prices. Crucially, productive survivors operate for a month longer during the crushing season. At 148 days, they are

already working for the entire length of the crushing season which typically lasts for 5 months between November and April. This leaves them with little room to absorb any of the reallocated cane from exiting mills. Taking in more volume at baseline installed capacity would mean processing cane that is past its optimal maturity with direct consequences for sugar recovery and revenues. Marginal survivors, on the other hand, do not face such a constraint.

**Table 2:** Reallocation of cane to surviving mills depends on capacity constraints

| | Productive Survivors | Marginal Survivors | $H_a : \Delta \neq 0$ |
|---|---|---|---|
| Sugar Recovery (%) | 10.58 | 9.52 | 1.06*** |
| Cane Crushed ('000 tonnes) | 556 | 347 | 208*** |
| Installed Capacity (TCD) | 4,250 | 3,350 | 900*** |
| **Crushing Duration (days)** | **148** | **118** | **30*** ** |
| Daily Capacity Utilisation (%) | 87.9 | 87.0 | 0.90 |
| Mills in 50 km Radius | 5.8 | 5.2 | 0.60* |
| Is Cooperative | 0.44 | 0.46 | -0.02 |
| Age (years) | 31.5 | 26.4 | 5.1*** |
| Number of Workers | 658 | 472 | 186*** |
| Wages ('000 INR) | 123 | 122 | 1.00 |
| Cane Prices (INR/tonne) | 2,133 | 1,983 | 150*** |

*Notes:* The table reports mean outcomes for productive and marginal survivors at baseline before experiencing an extreme drought. Productive (marginal) survivors are defined as plants that have operated every year from -5 to +10 years around a drought and have above (below) median sugar recovery over the two years preceding the drought. Prices are deflated using 2011 as the base year. $p$-values are from two-sided $t$-tests.

This distinction is central to the reallocation result that follows. When exiting mills' cane is redistributed to surviving mills, marginal survivors can absorb the additional volume because they have the capacity to run for another month, which productive survivors do not. Physical capacity expansion, which requires adding a new crushing tandem and installing additional boilers, requires lumpy capital investment and typically takes 4-5 years from planning to realization[18], ruling it out as a short-to-medium run response, especially after facing a significant decline in profits when confronted by an extreme

[18]Data on applications for capacity expansion by the universe of sugar mills in Maharashtra shows a 4-5 year lag on average between application dates and realized expansion. This lag arises due to challenges with land acquisition for expansion and construction of new, large processing units. Responses from the online mill survey in Maharashtra also point towards poor finances in the aftermath of droughts as a critical factor behind a slowdown in expansion plans for productive survivors.

drought. The reallocated cane therefore flows disproportionately to marginal survivors, not because of any spatial proximity advantage, but because they are the mills with room to accommodate additional cane.

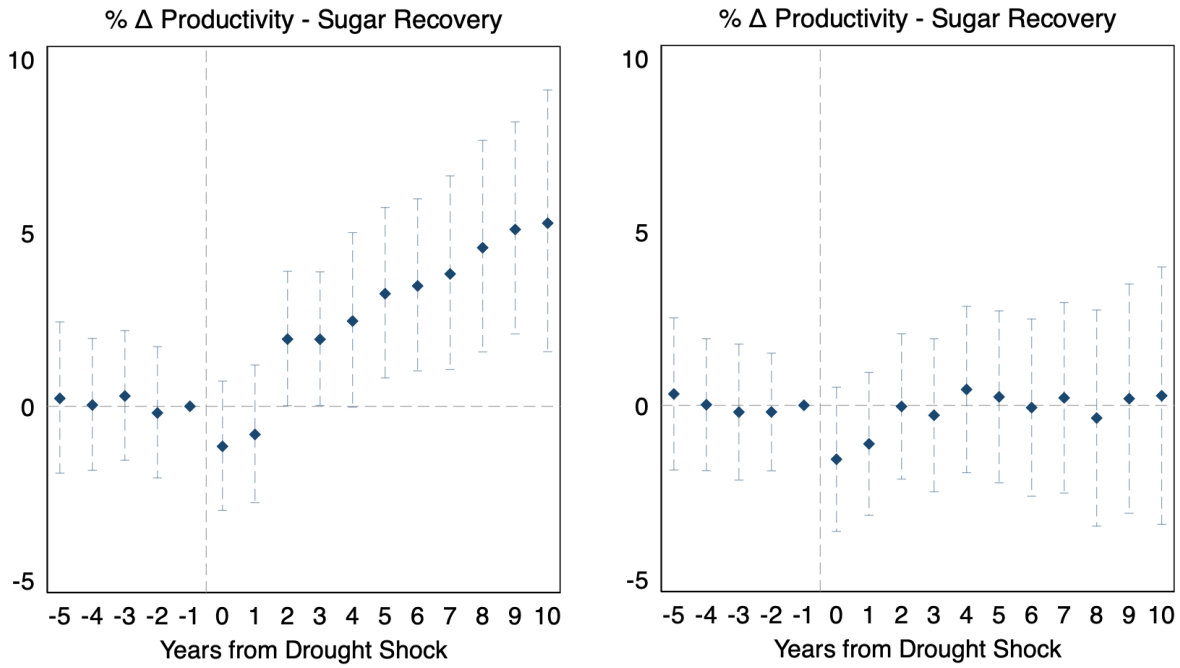
Taken together, these results show that the volume windfall from mill exit accrues almost entirely to marginal survivors. They expand procurement by around 20 percent, while capacity-constrained productive survivors, who are already crushing for the full season and unable to add capacity in the short-to-medium run, see little change in scale. Drought-induced reallocation thus raises scale precisely where there is room to grow.

### 5.3.2 Result 4: Sugar recovery rises for marginal survivors in the long-term, driven primarily through improved cane managment

I next turn to how mill productivity responds to reallocation of cane. I focus on marginal survivors — the mills that absorb the cane windfall from exit — and measure productivity using sugar recovery.

**Figure 15:** Marginal survivors observe a long-term growth in sugar recovery

**Panel A:** Sugar Recovery - Marginal Survivors **Panel B:** Sugar Recovery - Productive Survivors

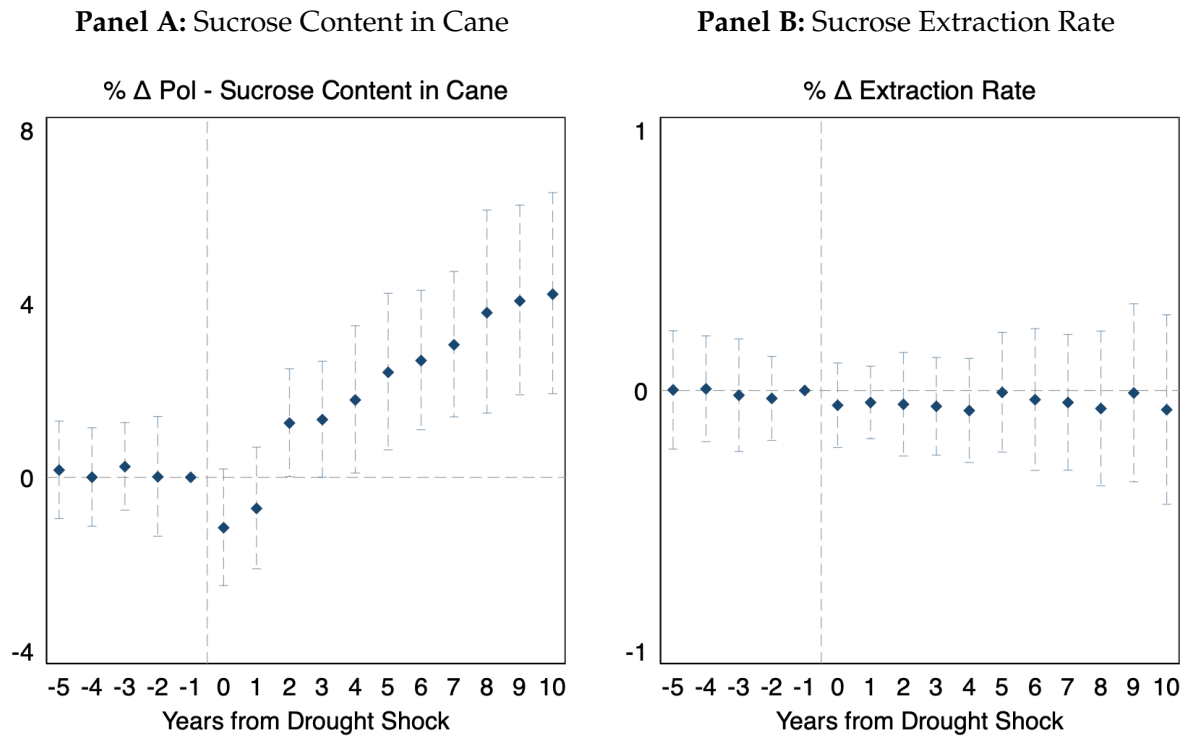



*Notes:* Panels A and B present event-study coefficients from Equation 2 using the Sun and Abraham (2021) estimator on plant-level sugar recovery for marginal survivors and productive survivors respectively. *Source:* Plant-level Records from the Indian Directorate of Sugar.

Figure 15, Panel A presents event-study estimates of the effect of droughts on sugar recovery for marginal survivors. Recovery is flat in the years preceding the drought and begins to rise about two years after it, climbing steadily to around 5% above baseline

over the long run. Panel B presents the same estimates for productive survivors, and reveals that they show no growth in recovery after the drought. This difference in estimates mirrors the reallocation result – the mills that absorb the volume windfall from exit are precisely the ones whose productivity improves – indicating that the gain in scale translates into a lasting improvement in how efficiently marginal survivors convert cane into sugar. I now show that this gain is achieved not through new processing technology, but through better management of cane quality.

**Figure 16:** Marginal survivors see a rise in cane's sucrose content



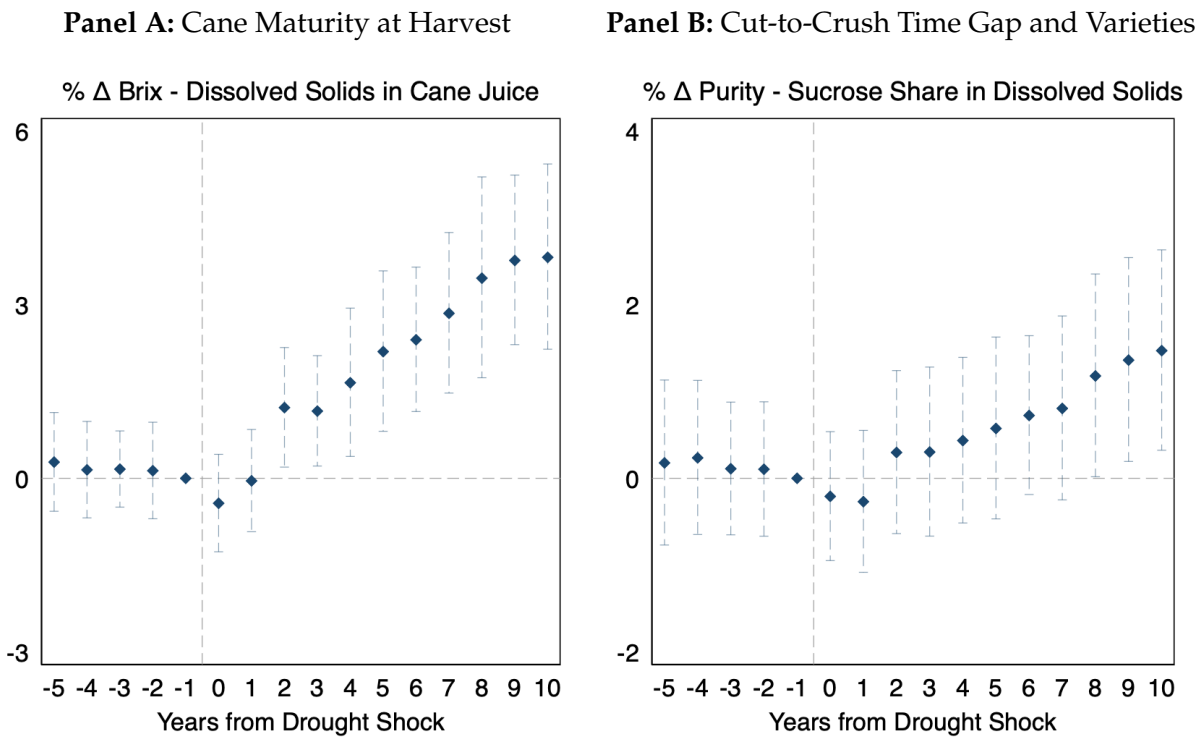

*Notes:* Panel A and B present event-study coefficients from Equation 2 using the Sun and Abraham (2021) estimator on plant-level sucrose content and extraction rate for marginal survivors. 95% confidence intervals are computed based on standard errors clustered at the district level. *Source:* Plant-level Records from the Indian Directorate of Sugar.

**Cane management upgrading.** Sugar recovery is the product of two stages: the sucrose content of the cane that arrives at the mill gate, and the efficiency with which the plant extracts that sucrose. The flowchart introduced in Section 2.2 and reproduced in Figure 3 lays out this decomposition, and I examine each component in turn. Sucrose content in cane, measured in the data as *Pol %* – the percentage of sucrose by weight of cane – rises by about 5% over the long run for marginal survivors (Figure 16, Panel A). This effect is absent for productive survivors. The extraction rate, by contrast – the share of available sucrose the plant actually recovers – which reflects milling machinery and processing technology, is flat throughout for marginal survivors and statistically indistinguishable from zero (Figure 16, Panel B). The entire recovery gain for marginal

survivors therefore originates upstream, in cane quality management, rather than downstream in the processing technology.

Consistent with this, I find no accompanying increase in capital stock for marginal survivors (Appendix Figure A.14), which rules out plant modernization as the source of the gain. The gain is also not explained by a change in ownership. Figure A.15 shows no effect of drought on mill ownership, ruling out acquisition or conversion between cooperative and private status as the source of the recovery improvement.

**Figure 17:** Marginal survivors' recovery gain is driven by improvements in cane quality management




*Notes:* Panel A and B present event-study coefficients from Equation 2 using the Sun and Abraham (2021) estimator on plant-level Brix and Purity for marginal survivors. 95% confidence intervals are computed based on standard errors clustered at the district level. *Source:* Plant-level Records from the Indian Directorate of Sugar.

What, then, raises the sucrose content of the cane? Pol % is itself the product of two measured components: *Brix*, the concentration of total dissolved solids in cane juice, and *Purity*, the share of those dissolved solids that is sucrose. Essentially, *Brix* measures cane maturity at harvest, since riper cane carries a higher dissolved-solids load. Similarly, *Purity* captures how much of that load is sucrose rather than having inverted into non-recoverable glucose and fructose, which depends on the time elapsed between cutting and crushing and on the cane variety. Both rise after the drought: *Brix* increases by roughly 4% (Figure 17, Panel A) and *Purity* by about 1.5% (Figure 17, Panel B). Together they point to three concrete improvements in how marginal

survivors manage cane quality. They harvest cane closer to peak maturity, compress the cut-to-crush interval so that less sucrose inverts before processing, and procure higher-sucrose varieties. These effects are absent for productive survivors.

These mechanisms are corroborated by the online survey of sugar mills in Maharashtra. In response to droughts, mills report using portable polarimeters to check cane maturity more frequently, and undertaking logistical planning of the crushing schedule – practices that map directly onto the increases in brix and purity documented above. The varietal channel finds independent support in the fibre content of cane, which declines over the same horizon (Appendix Figure A.16). Because improved cane varieties combine higher sucrose with lower fibre, the falling fibre share corroborates a shift toward better varieties rather than a change in harvest timing alone. Cultivation of drought-resistant varieties also grows in response to droughts (Figure A.17).

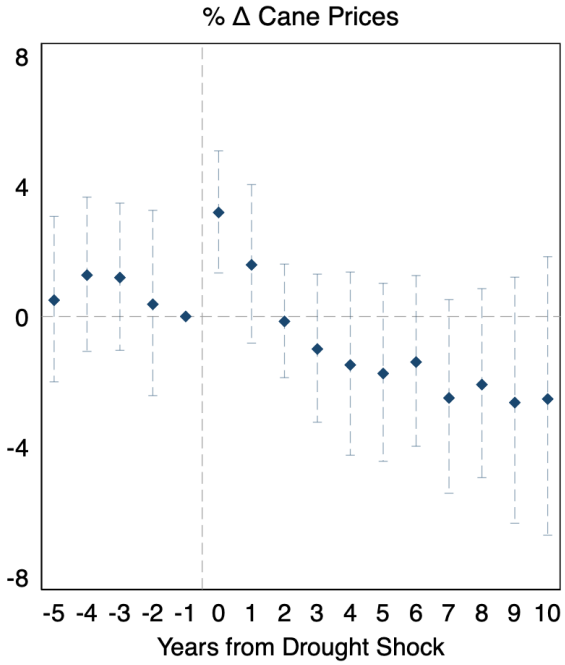
Taken together, these results show that marginal survivors—the mills that gain scale from reallocation—achieve lasting growth in sugar recovery, and that this gain operates entirely through better cane-quality management rather than new processing technology. Productive survivors, who absorb little additional cane, show no such improvement on any margin. The contrast is suggestive of a complementarity between scale and management upgrading: the returns to upgrading cane quality are realized only by the mills whose volumes expand.

#### 5.3.3 Result 5: Cane prices fall in the long-term despite within-mill gains, suggesting a rise in surviving mills' buyer power

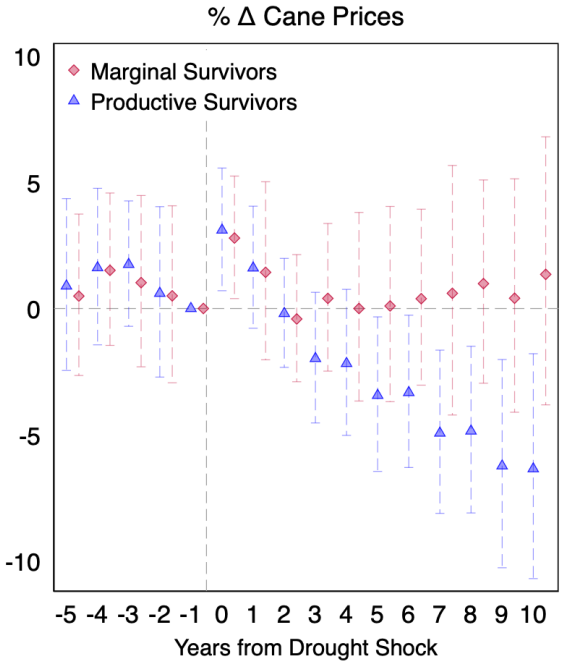
Figure 18, Panel A presents event-study estimates of the effect of droughts on farm-gate cane prices for the full sample of sugar mills. Prices rise by 3-4% immediately after the drought reflecting competition for scarce cane when a drought hits and decimates cane supply. In the long-term, however, cane prices appear to fall by 3%, although this effect is not statistically different from zero. Panel B breaks down the aggregate effect on prices into separate effects for productive and marginal survivors. In the short-term, prices rise similarly for both groups of survivors. In the long-term, the decline in prices appears to be driven entirely by the productive survivors. This points to cane rationing by capacity-constrained mills, who lower prices until cane supply falls to their capacity limit. For marginal survivors, rising sugar recovery would be expected to push cane prices up. Instead, prices are flat in the long-term, indicating wider markdowns as these mills face a less elastic residual supply curve with fewer competitors operating in these markets. Together, these effects suggest increased buyer power in more concentrated cane markets. Worker wages see no response though, suggesting competitive labour markets (Figure A.18).

**Figure 18:** Cane prices decline in the long-term

**Panel A:** Log Cane Prices - Full Sample




**Panel B:** Log Cane Prices - Heterogeneity




*Notes:* Panels A presents event-study coefficients from Equation 2 using the Sun and Abraham (2021) estimator on plant-level cane prices for the full sample. Panel B breaks the aggregate effect down into separate effects for productive and marginal survivors. 95% confidence intervals are computed based on standard errors clustered at the district level. *Source:* Plant-level Records from the Indian Directorate of Sugar and the Annual Survey of Industries.

## 5.4 Farmers

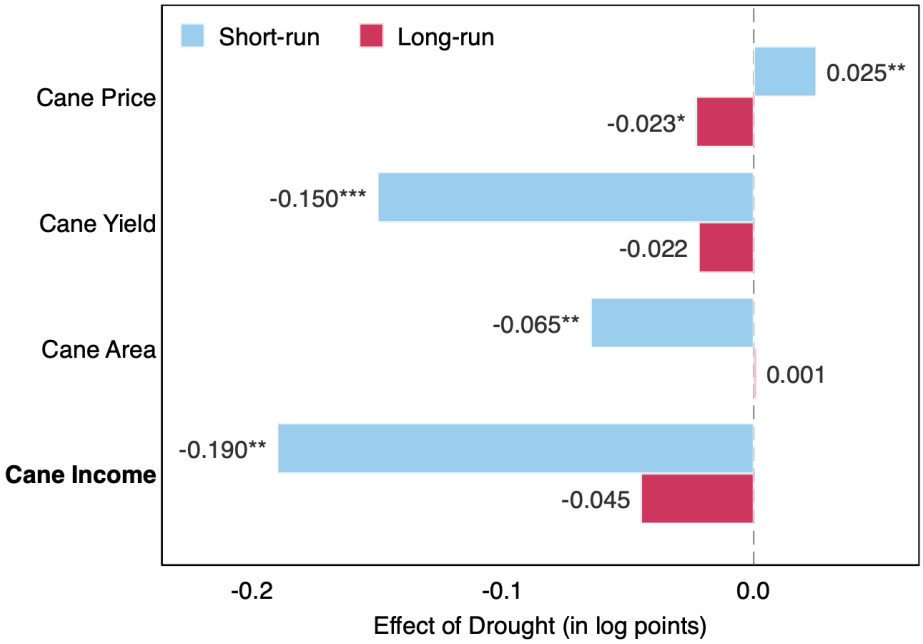
Finally, I look at the effect of droughts on farmers' cane income using farmer-level data from the Cost of Cultivation Surveys (CCS). I match each farmer to their potential buyer mill by identifying the sugar mill located closest to the farmer's village which are observable in CCS. The CCS covers a 15-year window from 2005 to 2019, shorter than the 1990-2025 span of the plant-level data, and I estimate the effect of droughts on cane income and its components using the event-study specification in Equation 2.

### 5.4.1 Result 6: Lower cane prices explain one half of long-term income losses for farmers, on par with yield losses themselves

Figure 19 decomposes the effect of droughts on farmers' cane income into its three components – cane price, yield, and acreage – measured at the farmer level and reported for both the short and long run. Because cane income is the product of price, yield, and acreage, the three channels account additively for the total log income effect. In the short run, drought cuts cane income sharply, by about 17 percent. The loss is

driven overwhelmingly by the supply side: yields fall by 14 percent as water stress damages the standing crop, and acreage contracts by 6 percent. Farm-gate prices move in the opposite direction, rising by around 2.5 percent as mills compete for scarce cane. Reassuringly, this effect is quantitatively similar to the short-term impact observed in Figure 18, which used cane price data from the Annual Survey of Industries. The short-run burden of drought on farmers is thus almost entirely a quantity shock.

**Figure 19:** Lower cane prices explain one half of long-term cane income losses




*Notes:* This figure presents coefficients on farmer cane income and its three components, by aggregating event-study estimates using the Sun and Abraham (2021) estimator for the short- and long-term. *Source:* The Cost of Cultivation Surveys (CCS).

The long-run pattern is qualitatively different, and it is where market structure becomes central. In the long-term, the supply-side channels have largely recovered: yields have returned nearly to baseline with a statistically insignificant 2 percent decline, and acreage is fully restored. Yet cane income remains depressed, by about 4.4 percent, and this persistent loss is now accounted for in roughly equal measure by prices and yields. Cane prices fall by 2.3 percent in the long run, again similar to the effect observed in Figure 18. Lower cane prices thus explain one half of farmers' long-term income losses, on par with the yield losses themselves. This is the central empirical fact the paper seeks to explain – that droughts inflict a lasting, market-mediated penalty on farmers even after their fields have recovered.

## 5.5 Summary of Empirical Results

The empirical analysis establishes six findings that together trace a single causal chain from a drought shock, through the restructuring of the cane market, to a redistribution of welfare between mills and farmers:

(i) Drought contracts cane supply in affected markets for up to two years.

(ii) The least productive mills exit, and their farmers reallocate to nearby surviving mills.

(iii) The reallocated cane flows disproportionately to marginal survivors, who – unlike capacity-constrained productive survivors – have the spare crushing capacity to absorb it.

(iv) Marginal survivors raise sugar recovery over the long run, driven primarily by improved cane management.

(v) Despite these within-mill productivity gains, cane prices fall in the long run, indicating a rise in surviving mills' buyer power.

(vi) Lower cane prices account for one half of farmers' long-term income losses – on par with the yield losses themselves.

These findings motivate and discipline the structural model developed in the next section. To be consistent with the evidence, the model must jointly generate three features: (1) that drought-induced exit and reallocation raise the scale, and hence the recovery, of capacity-unconstrained survivors; (2) that the same market thinning widens oligopsony markdowns, so that productivity gains are captured by mills rather than passed through to farmers; and, (3) that these two forces – rising productivity and rising buyer power – operate simultaneously on the cane price. Only a model embedding both the upgrading margin and the oligopsony margin can reconcile the coexistence of within-mill productivity growth with falling farm-gate prices, and thereby quantify the central trade-off this paper studies: the welfare gain from higher aggregate productivity against the distributional loss borne by farmers.

# 6 Model

## 6.1 Intermediary Cane Demand

### 6.1.1 Technology

Sugar mill $i$ in year $t$ produces sugar $Q_{it}$ using cane $M_{it}$, labour $L_{it}$, which are both expressed in quantities, and fixed assets $K_{it}$. I assume that cane cannot be substituted

with either labour or capital, so production is Leontief:

$$Q_{it} = \min \left\{ \beta_{it}^{M} M_{it}, \;\; \Omega_{it} H(L_{it}, K_{it}) \right\}. \tag{3}$$

The first arm corresponds to the amount of sugar recovered directly from cane: a tonne of cane yields $\beta_{it}^{M}$ tonnes of sugar, where $\beta_{it}^{M}$ is *sugar recovery*, the observable measure of mill productivity. The second arm is a labour-capital aggregate $H(\cdot)$, twice differentiable in both inputs with common parameterisation $\beta$, scaled by Hicks-neutral productivity $\Omega_{it}$. Processing capacity is bounded: cumulative crushing cannot exceed $\bar{M}_{it}$, the mill's maximum seasonal throughput, which I construct as the mill's installed crushing capacity (tonnes crushed per day) multiplied by the length of the crushing season in its state (days), inferred from manufacturing records:

$$M_{it} \;\leq\; \bar{M}_{it} \;\equiv\; \underbrace{\kappa_{it}}_{\text{Installed Capacity (TCD)}} \times \underbrace{D_{s(i)t}}_{\substack{\text{Season Length} \\ (days)}} \tag{4}$$

Departing from the common assumption that the conversion rate is homogeneous across firms (Rubens, 2023; Avignon and Guigue, 2025) or exogenous (De Loecker and Scott, 2016), I treat recovery as a plant-level *choice* which can be improved through cane-quality upgrading, motivated by the empirical results shown in Section 5. Upgrading is a discrete management decision $u_{it} \in \{0, 1\}$: a mill that adopts the cane-quality upgrading programme raises recovery by a factor $\gamma > 1$, at a fixed cost $F_{\text{up}}$,

$$\beta_{it}^{M}(u_{it}) = \left(1 + (\gamma - 1)\, u_{it}\right) \beta_{it}^{M} \;=\; \begin{cases} \beta_{it}^{M} & \text{operate as normal } (u_{it} = 0), \\ \gamma\, \beta_{it}^{M} & \text{upgrade } (u_{it} = 1). \end{cases} \tag{5}$$

Treating the conversion rate as heterogeneous and firm-chosen is the key institutional feature of agricultural processing, not only in sugar but in coffee, cotton, tea, and other goods, something that a homogeneous-recovery model omits. Equation 3 nests production functions in which all inputs are substitutable; the recovery parameter would then be zero, and cane would be an additional substitutable input in $H(\cdot)$.

I assume that cane and labour are variable inputs: their amount is chosen by mills in the same time period as when they are used. I also assume that cane and labour are static inputs, which means that they only affect current profits. These assumptions rule out adjustment costs over sugar and inventories. Capital is, in contrast, dynamic and fixed; the capital stock at time $t$ can only be changed through investment at time $t$ - 1.

### 6.1.2 The Mill's Problem

Each year, mills choose labour $L_{it}$, cane $M_{it}$, and the discrete upgrading decision $u_{it} \in \{0, 1\}$ to maximize current variable profits. Because labour and cane are complements, choosing labour pins down cane and hence output. Through their cane quantity choices, mills also set cane prices subject to a floor. Hence, cane farmers are assumed to be price-takers, which is intuitive given that there are many more farmers than sugar mills ($\sim$15,000 farmers per mill). Mills are price-takers in sugar and labour $(P_t^s, W_{it}^L)$ and oligopsonists in cane.

$$\Pi_{it} = \max_{L_{it},\, M_{it}} \max \Big\{ \underbrace{P_t^s \beta_{it}^M M_{it} - W_{it}^M M_{it} - W_{it}^L L_{it} - F_{\text{op}}}_{\text{operate as normal}}, \\ \underbrace{P_t^s \gamma \beta_{it}^M M_{it} - W_{it}^M M_{it} - W_{it}^L L_{it} - F_{\text{op}} - F_{\text{up}}}_{\text{upgrade } (\gamma>1,\ \text{pay } F_{\text{up}})} \Big\}, \tag{6}$$

where sugar revenue uses $Q_{it} = \beta_{it}^M M_{it}$ from (3), and $F_{\text{op}}$ is a fixed operating cost. The problem is subject to the capacity constraint and the statutory price floor, which has base price $\phi_0$ at reference recovery $\bar{\beta}^M$ and a recovery premium $\phi_1 > 0$:

$$M_{it} \;\le\; \bar{M}_i, \qquad W_{it}^M \;\ge\; \phi_0 + \phi_1 \big(\tilde{\beta}_{it}^M - \bar{\beta}^M\big), \tag{7}$$

where $\tilde{\beta}_{it}^M \in \{\beta_{it}^M, \gamma\beta_{it}^M\}$ is the mill's realized recovery. The floor is the Fair and Remunerative Price (or, in SAP states, the higher State Advised Price); its recovery-linked premium means an upgrading mill faces a higher mandated price. A mill operates only if its variable profit is non-negative; otherwise it exits ($\pi(\beta_{it}^M) < 0 \Rightarrow$ exit), withdrawing its cane demand and, as shown below, widening the markdowns of surviving rivals.

### 6.1.3 Input Prices and Markdowns

Solving the cane first-order condition delivers the cane-price markdown:

$$W_{it}^M = \frac{\varepsilon_{it}^s}{\varepsilon_{it}^s + 1} \Big( \text{NetMRP}_{it}^M - \lambda_{it} \Big), \qquad \text{NetMRP}_{it}^M \equiv \tilde{\beta}_{it}^M \Big( P_t^s - \tfrac{W_{it}^L}{\Omega_{it} H_L} \Big), \tag{8}$$

where $\text{NetMRP}_{it}^M$ is the marginal revenue product of cane net of the complementary labour cost of processing it, $\lambda_{it} \ge 0$ is the shadow value of the capacity constraint with $\lambda_{it}(\bar{M}_i - M_{it}) = 0$, and $H_L \equiv \partial H / \partial L$. The factor $\varepsilon_{it}^s / (\varepsilon_{it}^s + 1) < 1$ is the oligopsony markdown: a less elastic residual cane supply (lower $\varepsilon_{it}^s$) widens the markdown – for instance when drought-induced exit concentrates procurement on a surviving mill. The capacity multiplier depresses the price further: a mill at its crushing limit values

marginal cane only up to its processing value, so $\lambda_{it} > 0$ lowers $W_{it}^M$. When the floor binds the mill instead pays $W_{it}^M = \phi_0 + \phi_1(\tilde{\beta}_{it}^M - \bar{\beta}^M)$.

### 6.1.4 The Upgrading Decision

Upgrading is discrete: a mill upgrades iff the upgrade payoff in (6) weakly exceeds the operate-normally payoff. When the floor is slack the mill pays the markdown $W_{it}^M = \psi_{it}(P_t^s - W^L/\Omega H_L)\tilde{\beta}_{it}^M$ with $\psi_{it} \equiv \varepsilon_{it}^s/(\varepsilon_{it}^s + 1)$, keeping only the $(1 - \psi_{it})$ share of the value it creates; the labour and operating terms cancel and the decision reduces to

$$\begin{aligned} (1-\psi_{it})\left(P_t^s - W^L/\Omega H_L\right)(\gamma-1)\,\beta_{it}^M\,M_{it} \;\geq\; F_{\text{up}} \quad &\Longleftrightarrow \\ M_{it} \;\geq\; M_{it}^* \equiv \frac{F_{\text{up}}}{(1-\psi_{it})\left(P_t^s - W^L/\Omega H_L\right)(\gamma-1)\,\beta_{it}^M} \end{aligned} \tag{9}$$

Two implications follow.

(i) **Scale-Upgrading Complementarity.** The upgrade benefit is increasing in cane volume, so only mills above the threshold $M_{it}^*$ upgrade. Reallocation of cane towards survivors raises their scale and pushes them past the threshold, so absorbing mills upgrade and aggregate recovery rises with concentration.

(ii) **Buyer Power.** The benefit also scales with the captured share $(1 - \psi_{it})$, which is larger when residual supply is less elastic. Greater buyer power lowers $M_{it}^*$, so the same restructuring that raises a survivor's scale also raises the share of the upgrading gain it retains.

*Market restructuring thus raises both the incentive to upgrade (scale $M$) and the power to capture the gains (the markdown share $1 - \psi$), pushing survivors past $M^*$.*

### 6.1.5 Cane Input Demand

Inverting the labour condition under a slack price floor and slack capacity gives optimal labour, and substituting into (3) delivers the cane input-demand function which is truncated at $\bar{M}_i$ when capacity binds.

$$M_{it}^* = \frac{1}{\tilde{\beta}_{it}^M}\left(\Omega_{it}\,(\beta^L)^{\beta^L}K_{it}^{\beta^K}\left[\frac{P_t^s - \frac{W_{it}^M}{\tilde{\beta}_{it}^M}\left(\frac{\varepsilon_{it}^s+1}{\varepsilon_{it}^s}\right)}{W_{it}^L}\right]^{\beta^L}\right)^{\frac{1}{1-\beta^L}} \tag{10}$$

Compactly, $M_{it} = m\big(P_t^s, W_{it}^M, W_{it}^L, K_{it}, \beta^L, \beta^K, \tilde{\beta}_{it}^M, \Omega_{it}, \varepsilon_{it}^s\big)$, which is strictly monotone in productivity $\Omega_{it}$. Except the production parameters $(\beta^L, \beta^K, \Omega_{it})$, all other parameters on the right-hand side $(P_t^s, W_{it}^M, W_{it}^L, L_{it}, K_{it}, \tilde{\beta}_{it}^M)$ are observed, with $\varepsilon_{it}^s$ coming from the upstream supply model. Monotonicity in $\Omega_{it}$ makes (10) the proxy that inverts for

latent productivity in estimation using the control function approach of Ackerberg, Caves and Frazer (2015).

## 6.2 Upstream Cane Supply

Farmers face a nested discrete choice problem. In the inner nest, a farmer who has chosen to grow cane selects which mill to sell to. In the outer nest, the farmer decides whether to grow cane at all, or to allocate land to an alternative crop. The nesting structure ensures that mill exit affects farmers through two channels: it reduces the set of mills available (inner nest) and, through the inclusive value, reduces the attractiveness of cane relative to other crops (outer nest).

### 6.2.1 Environment

A market $d$ (a district-year) contains a unit mass of land plots indexed by $\omega$, with cultivable area $\bar{L}_d$. Each plot is operated by a farmer who allocates its use to the crop with the highest revenue per hectare. The choice set has two levels. At the outer level the plot is allocated to one of $K+1$ crops $k \in \{0, 1, \ldots, K\}$, where $k = 0$ denotes sugarcane and $k = K$ a reference crop. At the inner level, conditional on cane, the plot's output is sold to one of the mills $i$ from the local choice set $I_d \cup \{0\}$, where $\{0\}$ denotes an outside option (selling to a jaggery producer).

For a competing crop $k \geq 1$, revenue per hectare is $\mathcal{R}_k(\omega) = \tilde{p}_k \, \eta_k(\omega)$, where $\tilde{p}_k$ is the crop's effective output price and $\eta_k(\omega)$ is the plot's idiosyncratic productivity. For cane sold to mill $i$, revenue is $\mathcal{R}_{0i}(\omega) = P_i \, \eta_0(\omega) \, \nu_i(\omega)$, where $\eta_0$ is cane productivity, $\nu_i$ a plot–mill match shock, and $P_i$ the value of mill $i$ per efficiency unit of cane. I parameterize the log of this value as linear in observables,

$$\ln P_i \;\equiv\; \tfrac{1}{\theta}\,\delta_i, \qquad \delta_i(d,t) = \alpha \ln W_i^M(d,t) + \mathbf{x}_{it}'\boldsymbol{\gamma} + \xi_i(d,t), \qquad \delta_0 \equiv 0, \tag{11}$$

where $W_i^M$ is the cane price offered by mill $i$, and $\mathbf{x}_{it}$ captures observable mill characteristics. The coefficient $\alpha > 0$ governs the price response, and the term $\xi_i(d,t)$ captures unobserved mill-specific amenity.

*Nesting assumption.* Competing crop productivities are independent Fréchet, $\Pr[\eta_k \leq \eta] = \exp(-T_k \eta^{-\theta})$, with shape $\theta > 1$ and scale $T_k > 0$, independent across crops and plots. The cane revenues $\{\mathcal{R}_{0i}(\omega)\}_i$ are instead positively dependent within the cane nest: they share the common cane component $\eta_0(\omega)$, while the mill match shocks $\nu_i(\omega)$ are i.i.d. across mills. The strength of this within-nest dependence is governed by a dissimilarity parameter $\rho_0 \in (0, 1]$ ($\rho_0 = 1$ being independence). I take this correlation as a primitive, built into the joint distribution of cane revenues rather than derived

by adding shocks, consistent with what a nested GEV generator provides (McFadden, 1977). In logs, $\ln \mathcal{R}_{0i}$ is a deterministic term, an i.i.d. Gumbel mill shock at scale $\sigma$, and a common cane-nest component – a Cardell$(\rho_0)$ variate (Cardell, 1997) – that ties the mills together. Since the log of a Fréchet variate is Gumbel, revenue maximization in levels is equivalent to additive random-utility maximization in logs, so the Fréchet outer nest and the Gumbel inner nest are two levels of a single nested-GEV problem. I exploit this equivalence throughout: it delivers closed-form shares and, as shown below, a testable cross-parameter restriction.

### 6.2.2 Inner Nest: Mill Choice Conditional on Growing Cane

Under the nesting assumption above, the probability that a farmer sells to mill $i$ is:

$$s_{i|0}(d,t) = \frac{\exp(\delta_i/\sigma)}{\sum_{i' \in \mathcal{I}_d \cup \{0\}} \exp(\delta_{i'}/\sigma)} \tag{12}$$

where $\sigma > 0$ is the logit scale of the mill nest. The inclusive value of the cane nest summarises the expected payoff from the best available mill option:

$$IV_0(d,t) = \sigma \ln \left( \sum_{i \in \mathcal{I}_d \cup \{0\}} \exp(\delta_i/\sigma) \right) \tag{13}$$

This object has three properties that matter for the model. First, $IV_0$ is increasing in the number and quality of available mills: adding a mill strictly raises $IV_0$, and removing one (through exit) strictly lowers it. Second, $IV_0$ is increasing in any mill's cane price, since higher prices raise $\delta_i$. Third, $IV_0$ links the inner nest to the outer nest: it enters the crop choice as the effective cane price, so that changes in the mill landscape - exit, entry, or price changes - propagate to farmers' crop allocation decisions.

### 6.2.3 Outer Nest: Crop Choice on Heterogeneous Land

In the outer nest, the farmer allocates land to a crop $k \in \{0 \text{ (cane)}, 1, \ldots, K\}$ with the highest revenue. Following Costinot, Donaldson and Smith (2016), each plot has a vector of crop-specific productivities drawn from independent Fréchet distributions with location parameters $T_k(d)$ (capturing land suitability for crop $k$ in market $d$) and common shape parameter $\theta > 1$ (governing the dispersion of comparative advantage across plots). The share of land allocated to crop $k$ is:

$$s_k(d,t) = \frac{T_k(d) \cdot \tilde{p}_k(d,t)^\theta}{\sum_{k'} T_{k'}(d) \cdot \tilde{p}_{k'}(d,t)^\theta} \tag{14}$$

where $\tilde{p}_k$ is the effective price of crop $k$. For cane, the effective price is derived from the inclusive value: $\tilde{p}_0(d,t) = \exp(IV_0(d,t)/\alpha)$, which aggregates over all mill options weighted by their attractiveness. For alternative crops, $\tilde{p}_k$ is the market price.

The Fréchet structure captures heterogeneity in land suitability: some plots are well suited to cane (e.g., irrigated, alluvial soils) while others are better for soybean or pulses. The shape parameter $\theta$ governs the aggregate acreage response to price changes: higher $\theta$ means more plots are on the margin between cane and alternative crops, so a given price change induces a larger shift in acreage.

The cane supply in market $d$ to mill $i$ is:

$$C_i(d,t) = \bar{L}_d \cdot y_0(d,t) \cdot s_0(d,t) \cdot s_{i|0}(d,t) \tag{15}$$

where $\bar{L}_d$ is the cultivable land area, $y_0$ is yield per hectare, $s_0$ is the cane acreage share (from the outer nest), and $s_{i|0}$ is the within-cane mill share (from the inner nest).

Consistency of the two nests imposes a restriction that is central to interpretation and identification. Requiring (12) and (14) to arise from a single valid nested-GEV generator pins the dissimilarity to

$$\rho_0 = \frac{\theta\sigma}{\alpha} \in (0,1], \qquad \text{equivalently} \qquad \frac{\alpha}{\sigma} \geq \theta. \tag{16}$$

Economically, mills must be closer substitutes for one another than cane is for competing crops – the within-cane substitution elasticity $\alpha/\sigma$ weakly exceeds the across-crop elasticity $\theta$. I do not impose (16); I estimate its two sides separately and treat it as an overidentifying restriction on the nesting structure.[19]

### 6.2.4 Supply Elasticity

The own-price supply elasticity faced by mill $i$ combines two margins of farmer response:

$$\varepsilon_i^s = \underbrace{\frac{\alpha}{\sigma}(1 - s_{i|0})}_{\substack{\text{Within-cane margin:} \\ \text{steal farmers from rival mills}}} + \underbrace{\theta\, s_{i|0}(1 - s_0)}_{\substack{\text{Cross-crop margin:} \\ \text{pull farmers from other crops into cane}}} \tag{17}$$

The within-cane margin captures substitution among mills: when mill $i$ raises its price, it attracts farmers from competing mills, with the response governed by $\alpha/\sigma$ and proportional to $(1 - s_{i|0})$ - the share of cane farmers currently selling to other mills. The cross-crop margin captures substitution between cane and alternative crops: a higher

[19] A proof that $\rho_0 \leq 1$ is necessary and sufficient for a valid GEV generator, via McFadden (1977), is given in Appendix C.

cane price raises $IV_0$, pulling some plots from soybean or cotton into cane, with the response proportional to $s_{i|0}(1 - s_0)$.

The elasticity has a key comparative static for the paper's mechanism. When competitors exit following a drought, each surviving mill's within-cane share $s_{i|0}$ rises mechanically (fewer mills sharing the same farmers). This lowers $\varepsilon_i^s$ - the mill faces a less elastic residual supply - increasing its oligopsony power. This is the market power channel of drought-induced restructuring: exit raises concentration and widens the markdown that each surviving mill can extract.

### 6.3 Equilibrium

Given the regulated sugar price $P^s$, labour wage $w$, fixed costs $F_{op}$ and $F_{up}$, and the cane-price floor $\underline{W}^M$, a *market equilibrium* is a cane-price vector $\{W_i^M\}$, a set of mill decisions, and a set of farmer allocations such that:

1. **Farmers optimize.** Taking $\{W_i^M\}$ as given, each farmer chooses a crop (outer nest) and, conditional on cane, a mill (inner nest). These choices determine the residual cane supply $C_i$ and the supply elasticity $\varepsilon_i^s$ faced by each mill $i$.
2. **Mills optimize.** Taking its residual supply as given, each mill $i$ chooses labour, cane, whether to upgrade, and whether to exit, and sets the markdown price $W_i^M \geq \underline{W}^M$.
3. **The cane market clears.** Cane supply $C_d$ equals cane demand $M_d$ at $\{W_i^M\}$ in each market. Mills are price-takers in the sugar and labour markets, so only the cane market clears.

Since each $W_i^M$ enters both mill $i$'s demand and, through $\{\delta_{i'}\}$, all farmers' shares, 1-3 constitute a fixed point in $\{W_i^M\}$. I solve it by iterating on the price vector, exploiting the monotonicity of excess cane demand.

## 7 Estimation

### 7.1 Production Function

Taking the logarithm of the production function in (3) results in equation (18). As cane is assumed to be non-substitutable and a linear function of the sugar output, it does not enter the estimable production function. The production function coefficients $\beta$ need to be identified:

$$q_{it} = h(l_{it}, k_{it}, \beta) + \omega_{it}. \tag{18}$$

The "output price bias" of Klette and Griliches (1996) is taken into account because output is observed in physical units rather than as revenues. Labour is observed in physical units as well but potentially with error; rather than observing total hours worked of quality-adjusted labour $l_{it}$, I observe the number of employees without quality adjustment, $\tilde{l}_{it}$. Capital is measured in monetary values $\tilde{k}_{it}$. If latent differences in utilization of labour are correlated with mill productivity, this induces an "input price bias" as discussed in De Loecker et al. (2016). To address this concern, I add a function $a(\cdot)$ of wages per worker to the production function:

$$q_{it} = h(\tilde{l}_{it}, k_{it}, \beta) + a(w_{it}^{L}) + \omega_{it}. \tag{19}$$

### 7.1.1 Identification

In order to identify the production function, I impose timing assumptions on mills' input choices, as proposed by Olley and Pakes (1996). As was explained in Section 6.2.1, labour is assumed to be a variable and static input, whereas capital is fixed and dynamic. Hence, labour is assumed to be chosen at time $t$, after the productivity shock $\omega_{it}$ is observed by the mill, while capital investment is chosen at time $t$–1, before the productivity shock is observed.

The usual approach in the literature is to invert the intermediate input demand function to recover the latent productivity level $\omega_{it}$, which can be used to construct the innovation using a productivity law of motion (Levinsohn and Petrin, 2003; Ackerberg, Caves and Frazer, 2015). This approach hinges on productivity being the only latent, serially correlated input demand shifter. However, input demand varies due to markdown variation as well, as pointed out by Doraszelski and Jaumandreu (2021). This becomes a key concern in my setting given drought shocks lead to concentrated markets following exit of less productive mills, potentially altering cane price markdowns observed by surviving mills. The approach with input inversion can still be used when making additional parametric assumptions on the distribution of markdowns, as I do in my nested supply model. Alternatively, one can also impose more structure on the productivity transition process, with the benefit of allowing for fully flexible heterogeneity in markdowns.

I estimate the production function using the former approach with the benefit of allowing for endogenous exit (Olley and Pakes, 1996; Levinsohn and Petrin, 2003; Ackerberg, Caves and Frazer, 2015). I use cane as the flexible input for first stage inversion, and include cane price as an argument in the first stage regression, as explained below. I include the dynamic panel approach following Blundell and Bond (2000) as a robustness check in the Appendix (Table B.3).

**First stage.** The cane demand derived in (10) depends on cane price, sugar price, sugar recovery, and all other input prices and quantities, which are all observed. Cane demand also depends on the output elasticities of labour and capital, the markdown and on productivity, which are all latent.

$$M_{it} = m\left(P_t^s, W_{it}^M, W_{it}^L, K_{it}, \beta^L, \beta^K, \beta_{it}^M, \Omega_{it}, \mu_{it}\right) \tag{20}$$

The output elasticities $\beta^L$ and $\beta^K$ are assumed to be the same for all mills and time periods. Markdowns and productivity vary, however, across mills and time. Without making further assumptions on the distribution of at least one of these two variables, the scalar unobservable assumption is violated, and Ackerberg, Caves and Frazer (2015) is not identified. Input demand can vary due to productivity and/or markdowns.

However, given the nested supply model for cane, all variation in markdowns is captured by observed sugar and cane prices, and cane market shares. A similar assumption was made in De Loecker et al. (2016) for a setting in which there is only imperfect competition downstream. Therefore, I include sugar price $P_{it}^s$, cane price $W_{it}^M$, and market shares $s_{it} \equiv (s_{j|0}, s_0)$ in the first stage regression, which is given by (21). The market shares included are total cane market share, and the inner-nest cane market share. Measurement error $\varepsilon_{it}^q$ is assumed to be additive to the function $\phi_t(\cdot)$.

$$q_{it} = \phi_t\left(\tilde{l}_{it}, k_{it}, W_{it}^M, W_{it}^L, P_{it}^s, \beta_{it}^M, s_{it}\right) + \varepsilon_{it}^q \tag{21}$$

I estimate this model using a second-order polynomial in all inputs to purge measurement error and recover fitted $\hat{\phi}_{it}$. Productivity can then be recovered as a function of the data and estimable parameters.

$$\omega_{it} = \hat{\phi}_{it} - h(\tilde{l}_{it}, k_{it}, \beta) - a(W_{it}^L) \tag{22}$$

**Second stage.** I allow for endogenous exit by estimating an exit probability $\hat{p}_{it}^x$ using a probit regression of observed exit on all the variables in the input demand function. I allow for this exit probability to be endogenous to productivity, as proposed by Olley and Pakes (1996), and following the implementation of Collard-Wexler and De Loecker (2015). I also allow productivity to depend on a drought dummy, $\mathbf{D}_{it}$, to reflect changes in local market structure as in De Loecker (2013) and Braguinsky et al. (2015).

$$\omega_{it} = g\left(\omega_{i,t-1}, \hat{p}_{i,t-1}^x, \mathbf{D}_{it}\right) + \nu_{it} \tag{23}$$

The productivity innovation $\nu_{it}$ is given by the difference between productivity and its

expected value from the law of motion.

$$\nu_{it} = \omega_{it} - \mathbb{E}(\omega_{it}|\omega_{it-1}) \tag{24}$$

Since labour is static and capital is predetermined, the innovation $\nu_{it}$ is orthogonal to lagged labour and current capital, giving the moment conditions

$$\mathbb{E}\left[\nu_{it}\left(\tilde{l}_{i,t-1},\, k_{it},\, w^{L}_{it}\right)\right] = 0 \tag{25}$$

I impose a third-order polynomial function for $\omega_{it-1}$ and a linear function for $\hat{p}^{x}_{i,t-1}$ and $\mathbf{D}_{it}$ in the productivity law of motion, and block-bootstrap standard errors with 200 iterations.

### 7.1.2 Results

**Estimates.** The estimated output elasticities are in Table 3 below. The estimates using the control function approach are in Panel B, and are 0.710 and 0.323 for labour and capital respectively. These estimates are respectively lower and higher compared to the OLS estimates in Panel A, which are 0.775 and 0.303 for labour and capital. Both specifications have a scale parameter that is just above one. Estimates using the dynamic panel approach of Blundell and Bond (2000) are very similar and can be found in Table B.3.

**Table 3:** Production Function Estimates

| | **A. Ordinary Least Squares** | | **B. Control Function** | |
|---|---|---|---|---|
| | Estimate | SE | Estimate | SE |
| Output Elasticity of Labour | 0.775 | 0.012 | 0.710 | 0.094 |
| Output Elasticity of Capital | 0.303 | 0.004 | 0.323 | 0.028 |
| Scale Parameter | 1.078 | | 1.033 | |
| Observations | 10,610 | | 7,867 | |

*Notes:* Standard errors are block-bootstrapped with 200 iterations.

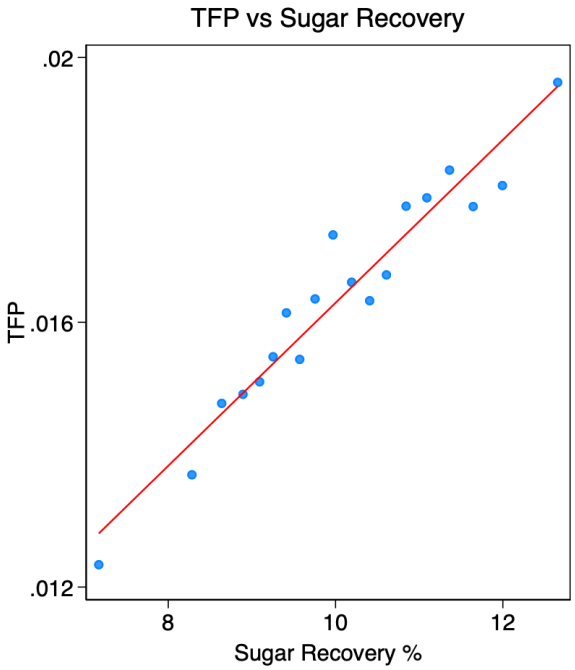
**TFP vs Sugar Recovery.** Next, I show that the estimated TFP correlates strongly with sugar recovery — the observed measure of mill-level productivity. Figure 20, Panel A validates sugar recovery as a measure of mill productivity and shows that the productivity gains documented in Section 5 are not an artefact of that particular measure. Panel A plots estimated plant-level TFP — recovered from the production-function estimation — against observed sugar recovery, and reveals a tight, near-linear relationship. Mills with higher recovery are systematically more productive in terms

of utilizing their labour-capital bundle to produce sugar, confirming that recovery is a faithful proxy for the latent productivity $\Omega$.

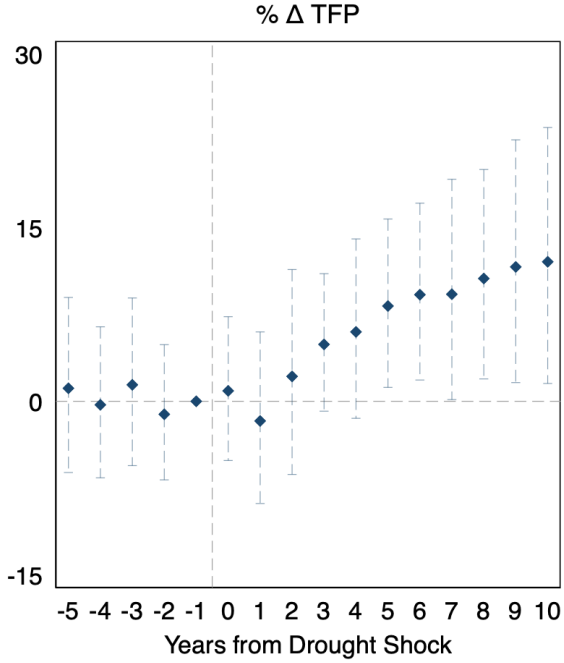
**Effects of Market Restructuring on TFP.** Figure 20, Panel B then re-runs the event study of Equation 2 with log TFP as the outcome for markets facing restructuring due to extreme droughts. The estimated path mirrors the recovery result closely. TFP is flat before the drought and rises steadily afterward, reaching 12% above baseline in the long run. The TFP gain reflects more efficient use of labour which I show in Appendix Figure A.18. In the long run, surviving mills procure more cane and produce more sugar while their workforce remains at pre-drought levels, so output rises relative to a flat labour input.

**Figure 20:** The two measures of mill productivity correlate strongly. TFP rises in response to drought-induced changes in market structure.

**Panel A:** Sugar Recovery and TFP




**Panel B:** Effect on Log TFP




*Notes:* Panel A shows the relationship between observed plant-level sugar recovery and estimated TFP. Panels B presents event-study coefficients from Equation 2 using the Sun and Abraham (2021) estimator on estimated plant-level TFP. 95% confidence intervals are computed based on standard errors clustered at the district level.

## 7.2 Supply Elasticities and Markdowns

I estimate the two parameters that govern farmers' supply responses: the within-cane (cross-mill) substitution elasticity $\alpha/\sigma$, which determines how readily farmers switch between mills, and the across-crop substitution elasticity $\theta$, which determines how readily land moves between cane and alternative crops. Together these pin down the

residual cane-supply elasticity each mill faces in Equation 17 and hence its markdown. I estimate each from the log odds implied by the corresponding nest, instrumenting the endogenous price with policy- and competition-driven shifters.

### 7.2.1 Within-Nest Substitution: Cross-Mill Elasticity $\alpha/\sigma$

Conditional on growing cane, the inner-nest shares (Equation 12) imply that the log odds of a farmer selling to mill $i$ rather than to the outside option (a jaggery producer, for which $\delta_0 \equiv 0$) are linear in the mill's cane price:

$$\ln\left(\frac{s_{i|0,dt}}{s_{0|0,dt}}\right) = \frac{\alpha}{\sigma}\ln W_{it}^{M} + x_{it}'\frac{\gamma}{\sigma} + \lambda_d + \lambda_{zt} + \tilde{\xi}_{it}, \tag{26}$$

where $s_{0|0,dt}$ is the share of cane farmers selling to the outside option in district $d$, $\lambda_d$ and $\lambda_{zt}$ are district and cane climatic zone-year fixed effects, and $\tilde{\xi}_{it} = \xi_{it}/\sigma$ is the unobserved mill amenity. The coefficient on $\ln W_{it}^{M}$ is the within-cane substitution elasticity $\alpha/\sigma$. Intuitively, $\alpha/\sigma$ is large when mills are close substitutes from farmers' perspective — when the idiosyncratic farmer–mill match shocks have little dispersion, so that small price differences reallocate large shares of cane.

Ordinary least squares is biased toward zero. The cane price $W_{it}^{M}$ is an equilibrium object: mills with higher unobserved amenity $\xi_{it}$ attract more cane and, through the markdown, set systematically different prices, inducing a simultaneity bias in $\alpha/\sigma$. I therefore instrument the cane price with two shifters that move the price a mill offers but are excluded from a farmer's idiosyncratic valuation of that mill: (i) the *number of competing mills within a 50 km radius*, a competition shifter that raises the price a mill must offer as its residual supply becomes more elastic; and (ii) the *mill's statutory price floor* (the FRP, or the higher SAP in SAP states), a policy shifter that mechanically lifts the offered price for mills whose unconstrained markdown price lies below it. Conditional on the location and cane zone-time fixed effects, neither the count of nearby mills nor the statutory floor plausibly enters the unobserved amenity $\xi_{it}$, while both strongly shift the price — the first-stage Kleibergen–Paap Wald $F$-statistic is 152.1 in Table 4, far above conventional thresholds.

### 7.2.2 Across-Nest Substitution: Cross-Crop Elasticity $\theta$

In the outer nest, the Fréchet crop shares (Equation 14) imply that the log odds of allocating a district's land to a crop $k$ rather than to a benchmark crop $K$ are linear in the effective-price gap between the two:

$$\ln\left(\frac{s_{k,dt}}{s_{K,dt}}\right) = \theta\Big(\ln \tilde{p}_{k,dt} - \ln \tilde{p}_{K,dt}\Big) + \lambda_d + \lambda_{zt} + \nu_{dt}, \tag{27}$$

where $\tilde{p}_{k,dt}$ is the market price of a non-cane crop $k$ and $\tilde{p}_{K,dt}$ is the market price of the benchmark crop *maize*. The district fixed effects absorb land suitability $T_k(d)$. The coefficient on the effective-price gap is the across-crop substitution elasticity $\theta$, which is large when many plots are marginal between competing crops (so acreage responds strongly to relative prices) and small when comparative advantage across crops is sharply drawn.

As in the inner nest, OLS is biased toward zero. Unobserved land-suitability and payoff shocks raise both a crop's acreage share and its price. I instrument the relative return to competing crops with two policy-driven shifters: (i) the crop's *minimum support price (MSP)*, the price at which the government commits to procure, set administratively at the national level and so orthogonal to a district's idiosyncratic suitability shocks; and (ii) the *share of the crop in the district procured by the government at the MSP*, which measures how binding the support price is locally and, therefore a measure of a district's exposure to the policy. Together they shift the attractiveness of alternative crops, and hence the cane acreage share, without being driven by local land productivity. The first-stage Kleibergen–Paap Wald $F$-statistic is 42.5 in Table 4.

I estimate Equation (26) on the mill-year panel from 1990-2025 and Equation (27) on the crop–district–year panel of land allocations using data on 14 most widely grown crops in the 226 cane markets. I use district and cane zone–year fixed effects throughout.

### 7.2.3 Results

**Estimates.** Table 4 reports the supply estimates. Panel A gives the cross-mill elasticity $\alpha/\sigma$: the OLS estimate of 1.067 rises to 6.204 under IV, the large gap reflecting the simultaneity bias toward zero that the instruments correct. The IV estimate implies that mills are highly substitutable from farmers' perspective, so that the exit of competitors sharply raises a surviving mill's residual market share and thereby its buyer power. Panel B gives the cross-crop elasticity $\theta$: OLS of 0.450 rises to 2.120 under IV. This estimate sits comfortably within the 1.5–2.5 range that the agricultural-trade literature reports for substitution across commodities (Costinot, Donaldson and Smith, 2016; Bergquist et al., 2022; Sotelo, 2020; Pellegrina, 2022; Dominguez-Iino, 2026), lending external validity to the outer-nest estimates.

The two IV estimates independently satisfy the nested-GEV restriction $\alpha/\sigma \geq \theta$ derived in Appendix C: $6.204 \geq 2.120$. The implied dissimilarity parameter is $\rho_0 = \theta\sigma/\alpha = 2.120/6.204 = 0.34 \in (0, 1]$. Mills are thus closer substitutes for one another than cane is for competing crops, exactly the ordering the nesting requires. Because I estimate the two sides of the restriction separately rather than imposing it, its satisfaction is an over-identifying test that the nested structure passes.

**Table 4:** Supply-side Substitution Elasticities

| | **A. Cross Mill Substitution** | | **B. Cross Crop Substitution** | |
|---|---|---|---|---|
| | OLS | IV | OLS | IV |
| $\alpha/\sigma$ | 1.067*** | 6.204*** | | |
| | (0.176) | (1.217) | | |
| $\theta$ | | | 0.450*** | 2.120*** |
| | | | (0.061) | (0.340) |
| District FE | ✓ | ✓ | ✓ | ✓ |
| Cane Zone-Year FE | ✓ | ✓ | ✓ | ✓ |
| Observations | 8,618 | 8,618 | 21,178 | 21,178 |
| KP Wald $F$-statistic | | 152.1 | | 42.5 |

*Notes:* Standard errors are clustered at the district level.

**Markdowns.** Estimated markdown is 1.20 at the average sugar mill, and 1.18 at the median sugar mill. This implies that farmers selling to the average mill receive around 83% of cane's marginal revenue product. This number is largely comparable to figures for other agricultural goods in the literature as can be seen in Table 5. Figure **??** shows how inverse cane markdowns vary as a function of local market structure.

**Table 5:** Average Markdowns in Agricultural Goods

| Paper | Markdown | Input |
|---|---|---|
| Rubens (2023) | 2.90 | Tobacco Leaf |
| Zavala (2026) | 1.64 | Various Crops |
| Dominguez-Iino (2026) | 1.35 | Cattle |
| **This Paper** | **1.20** | **Sugarcane** |
| Avignon and Guigue (2025) | 1.19 | Raw Milk |
| Dominguez-Iino (2026) | 1.16 | Maize, Soybean |
| Crespi and Sexton (2005) | 1.10 | Cattle, Potato, Rice |

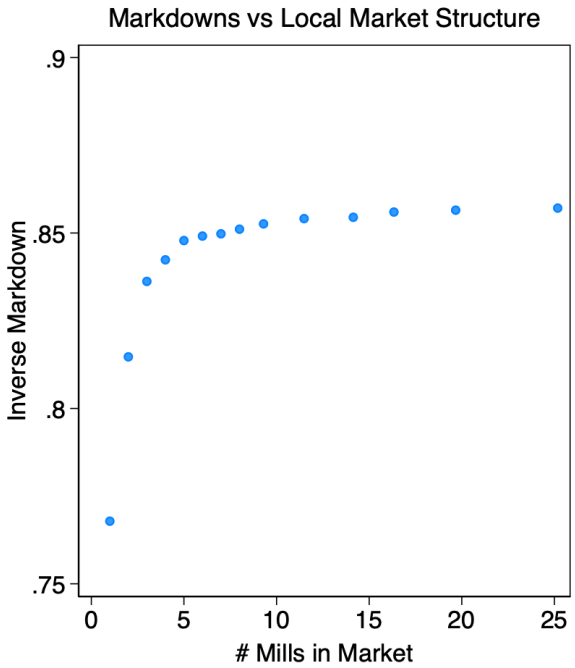
**Markdowns vs Market Structure.** Figure 21 provides direct evidence for the oligopsony channel at the heart of the mechanism. Panel A plots the estimated inverse markdown — the share of cane's marginal value that mills pass on to farmers — against the number of mills in the local market. The relationship is sharply increasing and concave: in near-monopsony, mills retain a large wedge and pay farmers only 77% of cane's marginal value. This share rises steeply as the first few competitors enter, and it flattens out above roughly ten mills. Buyer power is thus most acute precisely where markets are thin, exactly the configuration that drought-induced exit produces.

**Effects of Market Restructuring on TFP.** Figure 21, Panel B confirms that this operates dynamically. Re-running the event study of Equation 2 with the estimated cane

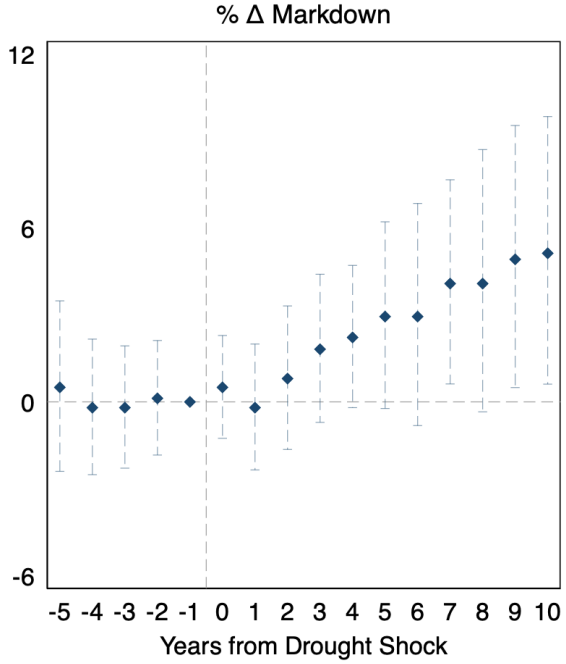
markdown as the outcome, markdowns are flat before the drought and widen steadily afterward, rising by 5% over the long run as exit concentrates procurement on surviving mills. Together, the cross-sectional gradient and the event-study path show that the thinning of local markets after a drought raises surviving mills' buyer power, which is what diverts the productivity gains away from farmers.

**Figure 21:** Cane markdowns correlate strongly with local market structure, and rise in response to drought-induced changes in market structure.

**Panel A:** Markdowns and Market Structure




**Panel B:** Effect on Cane Markdowns




*Notes:* Panel A shows the relationship between cane markdowns and local market structure. Panels B presents event-study coefficients from Equation 2 using the Sun and Abraham (2021) estimator on estimated cane markdowns. 95% confidence intervals are computed based on standard errors clustered at the district level.

## 7.3 Fixed Costs

### 7.3.1 Fixed Cost of Upgrading

A mill *upgrades* cane quality when it builds the organizational capital needed to manage a long crushing season: harvest schedules that cut each field close to peak maturity, field staff to enforce them, and cane-development work with growers. Mill staff turn over from one season to the next, so this capital has to be rebuilt every season.[20] Its cost therefore recurs, and the upgrading choice is static. I assume that upgrading costs a

[20]Mills from Maharashtra report losing 60% of field staff year-on-year, suggesting that organizational capital for cane harvesting has to be rebuilt every year.

fixed amount $F_i^{up} = \phi K_i$ that is proportional to installed capacity $K_i$, to reflect the fact that a larger plant needs more staff and more fields brought into the harvest schedule to keep a long season running. From Section 6, a mill upgrades if

$$u_{it} = 1 \iff \underbrace{\gamma\, P_{it}^S\, \beta_{it}^M\, M_{it}}_{G_{it}} - \varphi K_i + \sigma_O\, \varepsilon_{it} \geq 0, \qquad \varepsilon_{it} \sim \text{Logistic}, \tag{28}$$

where $G_{it}$ is the extra sugar revenue from upgrading, evaluated at the sugar price $P_{it}^S$ and the cane the mill crushes, $M_{it}$. Estimation proceeds in four steps: measure $u_{it}$, estimate $\gamma$, bracket $\varphi$ using revealed preference, and estimate the shock scale $\sigma_O$ by maximum likelihood.

**Step 1: Measuring upgrading.** Organizational capability is not observed directly. I define $u_{it} = 1$ when the mill's net crushing season lasts at least 125 days. The threshold comes from the production data rather than from assumption. Up to 125 days, a longer season mostly fills idle capacity. Beyond it, the mill is crushing cane further from peak maturity, which is when organization matters. Consistent with this, the slope of recovery in season length increases with the mill's share of skilled workers, and this increase shows a kink at 125 days (Figure A.19). Droughts move mills across the threshold by reallocating cane from exiting mills to survivors. Among mills in the bottom half of recovery that ran seasons shorter than 120 days before a drought, 44.4% run longer seasons in the long-term, against 32.2% of comparable mills in districts not yet hit by a drought (difference 12.1 points, s.e. 4.9).

**Step 2: The recovery gain $\gamma$.** I regress log recovery on $u_{it}$, and mill and cane-zone year fixed effects, excluding drought years 0 and 1. In those years seasons shorten because cane is scarce. I instrument $u_{it}$ with an indicator of whether the mill is in a post-drought period. As a result, $\gamma$ is identified from the same mill moving from short to long seasons, owing to drought-induced cane reallocation. The estimate is $\hat{\gamma} = 6.9\%$ (s.e. 0.4). Two alternatives bracket it. First, a DID comparison between bottom-half drought-district mills that cross the threshold and those that stay below it gives 10.6% (s.e. 2.9). This is an upper bound, because mills that cross may also improve in other ways. Second, the average long-run recovery gain of all bottom-half drought-district mills is 3.0% (s.e. 1.0), a lower bound because it averages over mills that do not upgrade. With $\hat{\gamma}$ in hand, recovery without upgrading is recovered as $\beta_{it}^0 = \beta_{it}^M / (1 + \hat{\gamma} \cdot u_{it})$, and $G_{it}$ can be computed for every mill-season, whether or not the mill upgraded.

**Step 3: Bracketing $\varphi$ by revealed preference.** The drought gives us a set of mills whose upgrading choice changes. I stack drought cohorts and take sugar mills in

drought districts that were in the bottom half of sugar recovery, that averaged seasons shorter than 125 days before the drought, and averaged at least 125 days in the long-term. Before the drought, these mills chose not to upgrade, so their gain per unit of capacity fell short of the cost: $G_i^{\text{pre}}/K_i < \varphi$. After the drought they upgraded, so $G_i^{\text{post}}/K_i \geq \varphi$. The gain rises mainly because these mills crush more cane. This supports the assumption that the switch reflects the change in $G$ rather than in $\varepsilon$. Taking medians across the crossing mills,

$$\text{Rs } 12{,}898 \;<\; \varphi \;\leq\; \text{Rs } 20{,}994 \quad \text{per TCD.}$$

I set $\varphi$ at the midpoint, Rs 16,946 per TCD. For the median mill (2,500 TCD), the fixed cost of upgrading is Rs 42.4 million per season, with a bracket of Rs 32.2–52.5 million.

**Step 4: The shock scale $\sigma_O$.** With $\varphi$ fixed, the probability of upgrading is $\Pr(u_{it} = 1) = \Lambda\big((G_{it} - \varphi K_i)/\sigma_O\big)$, which has a single unknown, $1/\sigma_O$. I estimate it by maximum likelihood on 10,718 mill-seasons outside drought years 0–1, of which 63.2% upgrade. The coefficient on the net gain is large and precisely estimated ($z = 47.9$), giving $\hat{\sigma}_O =$ Rs 13.1 million. As a check on Step 3, a logit that leaves the fixed cost free, $F_i^{up} = f_0 + \varphi K_i$, gives $f_0 =$ Rs 8 million and $\varphi =$ Rs 13,779 per TCD. That implies Rs 42.4 million at 2,500 TCD, the same as the bracket midpoint. The model fits the upgrading rate across the distribution of mills. Among mills in the bottom half of sugar recovery, 49.0% upgrade in the data and 45.8% in the model; in the top half, 75.3% and 76.0%. Table 6 collects the estimates of upgrading costs.

**Table 6:** Fixed Cost of Upgrading: Estimates

| | 125 days |
|---|---|
| Recovery gain $\gamma$ (within mill) | 0.069 (0.004) |
| Bracket for $\varphi$ (Rs per TCD) | 12,898–20,994 |
| $\varphi$, midpoint (Rs per TCD) | 16,946 |
| Fixed cost at 2,500 TCD (Rs million per season) | 42.4 |
| Free logit: $f_0$ (Rs million) + $\varphi$ (Rs per TCD) | 8 + 13,779 |
| Shock scale $\sigma_O$ (Rs million) | 13.1 |
| Mill-seasons in logit | 10,718 |
| Share upgrading | 0.632 |

*Notes:* Upgrading = net crushing season of at least the stated number of days. The $\varphi$ bracket uses the median gain per TCD of bottom-half drought-district mills that cross the threshold, before (lower end) and after (upper end) the drought. $\sigma_O$: logit with $\varphi$ fixed at the midpoint. Rupees deflated.

### 7.3.2 Fixed Cost of Operation

A mill that ran last season runs again if

$$\mathbb{E}[\pi_{it}] - F_{it}^{op} + \sigma\,\varepsilon_{it} \;\geq\; 0, \qquad \varepsilon_{it} \sim \text{Logistic}, \tag{29}$$

where $\pi_{it}$ is variable profit and $F_{it}^{op}$ is the *avoidable* fixed cost of operating. This is spending on seasonal staff, maintenance and overheads that does not depend on how much cane the mill crushes, which the mill pays if it runs and saves if it stays shut. Interest and depreciation are paid either way and do not enter the decision. Accounts do not separate the two kinds of fixed cost, but suspensions do. When a mill shuts for a season, its costs fall by its variable costs plus its avoidable fixed cost, and what it keeps paying is unavoidable.

**Suspension spells.** I compare each mill's total cost in the Annual Survey of Industries data for its last working season, $C_i^{\text{run}}$, with its total cost in the following suspended season, $C_i^{\text{idle}}$. I keep spells in which the mill crushed no cane while suspended, but operated in the year before. This leaves 254 spells in 196 mills. The variable cost per tonne of cane, $c$, is the slope of total cost on cane crushed with mill and cane zone-year fixed effects, estimated on 9,450 working mill-seasons. This gives $\hat{c} =$ Rs 2,558 (s.e. 64), mostly the cane purchase itself. The avoidable fixed cost of spell $j$ is

$$F_i^{op} \;=\; \left(C_i^{\text{run}} - \hat{c}\,M_i^{\text{run}}\right) \;-\; C_i^{\text{idle}}, \tag{30}$$

where $M_i^{\text{run}}$ is the cane crushed in the working season prior to suspension. The first term in parentheses is the working season's total fixed cost; the second removes the part the mill pays even when shut. The cost items behave as this decomposition requires Table 7. Idle mills still spend a median Rs 135 million a season. A median regression on installed capacity $K_i$ gives $F_i^{op} =$ Rs 16.1 million for a 2,500 TCD mill.

**Table 7:** Costs in the Last Working Season and the Suspended Season

| | Last working season | Suspended season | Median ratio |
|---|---|---|---|
| Materials | 304.8 | 2.4 | 0.01 |
| Labour | 57.4 | 36.7 | 0.60 |
| Maintenance | 6.1 | 0.8 | 0.23 |
| Interest | 82.5 | 65.3 | 0.86 |
| Depreciation | 15.6 | 12.3 | 0.89 |
| Total cost | 529.4 | 134.5 | 0.30 |

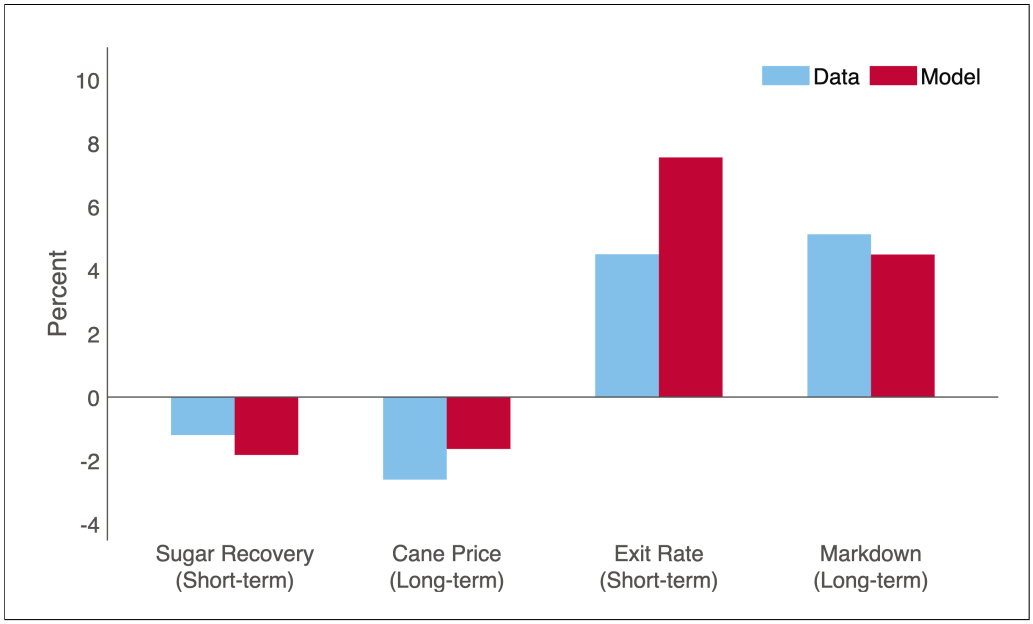
*Notes:* 254 suspension spells in 196 mills: a working season followed by a suspended season in which the mill crushed no cane. Medians across spells, Rs million, deflated. Median ratio: median across spells of suspended-season over working-season cost.

# 8 Aggregate Effects of Changes in Market Structure

To quantify the aggregate consequences of market restructuring that droughts set in motion, I run a counterfactual experiment inside the estimated model, across three periods. At $t = 0$, I solve the baseline equilibrium in the year before the drought across drought-affected markets. At $t = 1$ – the immediate aftermath of the shock, or the *short-term* – I impose a 15% yield shock to cane and a 5% yield shock to competing crops, matching the crop-specific yield responses recovered from event studies in Section 5, and re-solve for equilibrium allocations. Mills whose variable profits turn negative are assumed to exit permanently. At $t = 2$ – the long run – I return cane and competing-crop yields to their baseline levels but restrict the market to the mills that survived $t = 1$, and re-solve. This final period captures the economy at the new level of market concentration, with fewer mills operating. The simulation allows me to trace the economy's transition from the baseline equilibrium at t = 0 to the long-term post-shock allocation at t = 2 to evaluate aggregate effects.

## 8.1 Model Fit

**Figure 22:** Comparison of model and data estimaes



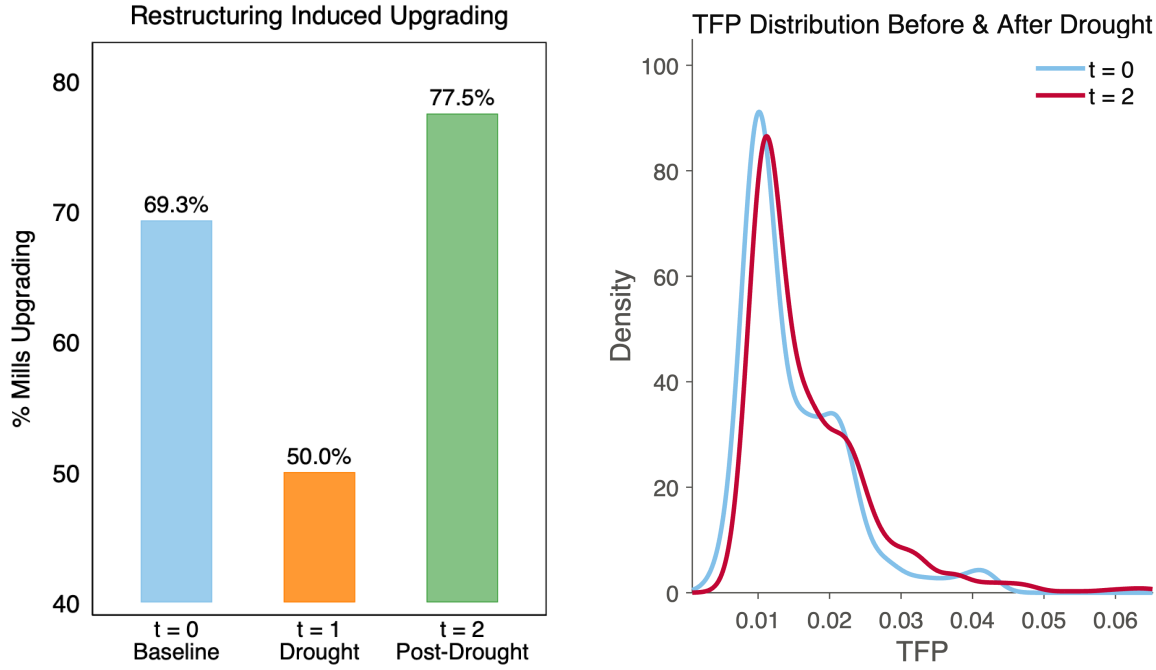

*Notes:* This figure compares model-predicted and empirical estimates of short- and long-term responses to drought shocks.

Figure 22 evaluates how well this simulation reproduces the empirical responses of sugar mills to drought shocks documented in Section 5. The estimation strategy does not target these moments directly. Rather, the model is entirely disciplined by pre-drought cross-sectional data, and yield shocks are simulated to reproduce event-study

responses. This exercise therefore provide an external validation of the model's ability to account for observed market- and mill-level adjustment patterns. The figure shows that the simulated model aligns closely with the data for four key outcomes: (1) Sugar recovery shows the short-run percent decline in mill-level recovery; (2) Cane price shows the long-run percent decline in farm-gate cane prices; (3) Exit rate shows the short-run percent decline in number of active mills; and (4) Cane markdown shows the percent increase in long-run markdowns imposed by mills on cane prices. I show model fit for targeted moments in Figure A.20 in the Appendix.

## 8.2 Productivity Decomposition

**Figure 23:** Market restructuring induced upgrading and productivity gains



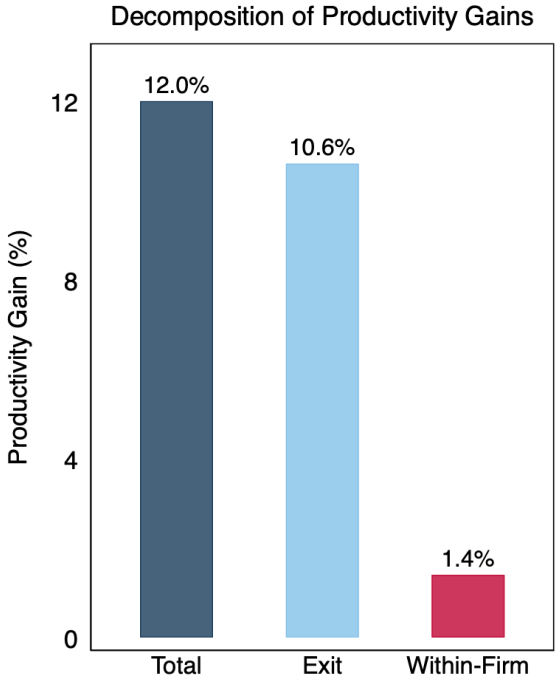

**Panel A:** Restructuring-induced Upgrading **Panel B:** TFP Distribution

*Notes:* This figure simulates a drought shock within the estimated model by simulating a drought-induced reduction in crop yields that matches event-study estimates from Section 5. Panel A tracks the share of sugar mills in impacted markets that engage in cane management upgrading in the short- and long-run. Panel B illustrates the aggregate productivity gains by presenting kernel density plots of the TFP distribution before and after the shock, highlighting shifts toward higher productivity due to two adjustments: within firm gains and extensive-margin effects due to exit.

Next, I look at how drought-induced market restructuring affects aggregate mill productivity. Figure 23 summarizes the mechanism. During the drought year, the share of mills undertaking cane management upgrading falls from 69.3% at baseline to 50% as cane supply shrinks and mills absorb the shock (Panel A). In the long run, however,

the exit of the weakest mills leaves survivors facing a more concentrated catchment with farmers from exiting mills reallocating to those nearby. This benefits the marginal survivors, who are capacity-unconstrained relative to productive survivors at baseline, and can therefore absorb the reallocated cane. This pushes them beyond the critical crushing season duration threshold that makes upgrading viable, and increases the long-term share of mills upgrading to 77.5%. This is the scale-management complementarity at work: restructuring raises marginal survivors' effective scale, which in turn raises their return to upgrading. Panel B shows kernel density estimates comparing the distribution of mills' total factor productivity between $t = 0$ and $t = 2$. The resulting rightward shift in the distribution reflects both the selective exit of low-productivity mills and the within-firm gains among survivors that upgrade.

**Figure 24:** Aggregate mill total factor productivity rises by 12% in the long-term




*Notes:* This figure decomposes the total productivity increase into two mutually exclusive components: selection and within firm gains, underscoring the distinct mechanisms through which aggregate mill productivity is enhanced in response to drought-induced market restructuring.

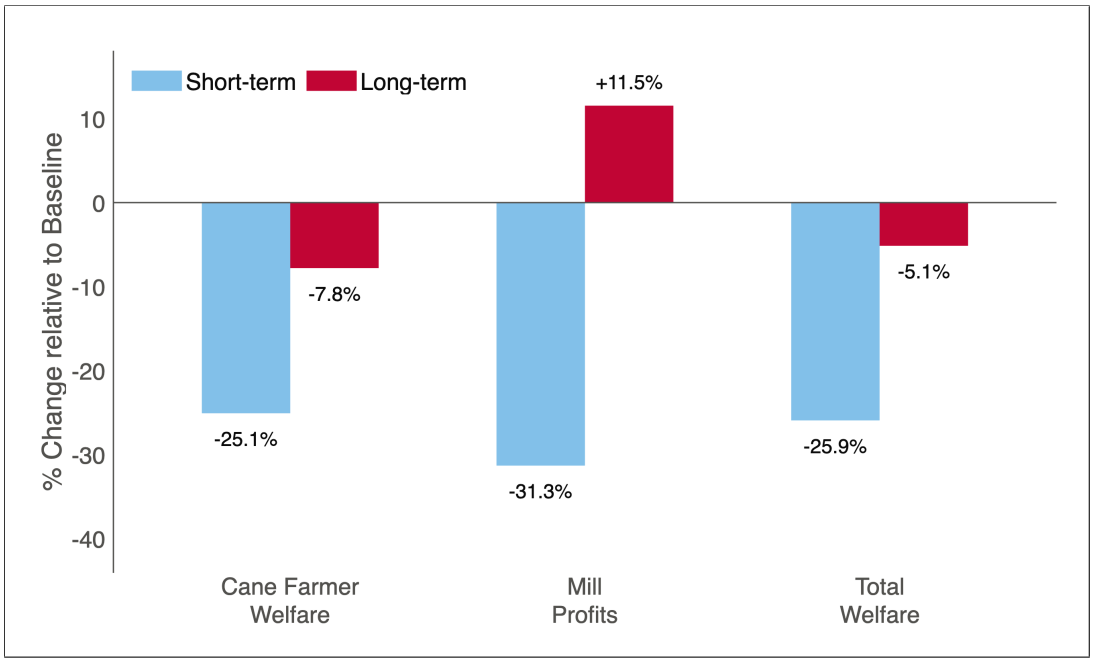
Figure 24 aggregates these adjustments. Long-run aggregate mill productivity rises by 12.0% relative to baseline. Decomposing this gain into its two mutually exclusive sources, selection through the exit of less productive mills accounts for 10.6 percentage points (about 88% of the total), while within-firm productivity improvements among surviving mills account for the remaining 1.4 percentage points (about 12%). The selection channel is the one emphasized in the canonical trade-and-heterogeneous-firms literature (Melitz, 2003). The within-firm channel is quantitatively smaller but economically distinct, since it raises productivity among mills that remain in the market

rather than by reallocating activity across them. These within-firm efficiency gains underscore the role that management upgrading, which is induced by drought-induced market restructuring, plays in enhancing aggregate productivity.

## 8.3 Welfare Decomposition

A productivity gain of this size would, in a frictionless setting, be unambiguously good news. Figure 25 shows that it is not. In the short run the drought is costly for everyone: cane-farmer welfare falls 25.1%, mill profits fall 31.3%, and total surplus falls 25.9% relative to baseline. In the long run, the incidence diverges sharply. Mill profits recover and end 11.5% above baseline, as the restructuring that raises productivity also raises concentration and widens the markdown each surviving mill can extract. Cane farmers do not share in these gains: their welfare remains 7.8% below baseline, because the exit of mills worsens their outside options and depresses the cane price they receive. On net, total welfare is still 5.1% below baseline in the long run.

**Figure 25:** Cane farmer welfare declines by 7.8% in the long-term




*Notes:* This figure decomposes changes in short- and long-term total welfare into cane farmer surplus and sugar mill profits.

The contrast between Figures 24 and 25 is the central lesson of this exercise. Drought-induced restructuring makes the processing sector more productive, but it does so largely by concentrating the market, and the resulting efficiency gains accrue to mills as higher profits rather than to farmers as higher prices. Evaluating the long-run impact of climate shocks through the lens of aggregate productivity alone would therefore miss

their first-order welfare consequence: a persistent transfer away from the smallholders at the base of the supply chain.

# 9 Conclusion

This paper shows that climate change impacts farmers not only by lowering crop yields, but also by restructuring the markets in which they sell. In the Indian sugar industry, extreme droughts cause the least productive mills to exit and their farmers to reallocate to nearby survivors. This reallocation is not merely compositional: by expanding the volume base over which quality improvements apply, it raises survivors' return to upgrading and triggers within-firm productivity growth. But the same concentration that funds upgrading also widens mills' buyer power: farm-gate cane prices do not rise, so the productivity gains are captured by mills rather than shared with the millions of farmers who supply the industry. Climate-induced adaptation and exploitation are thus complements, driven by a single change in local market structure.

These findings carry a broader lesson for how we think about climate change and agricultural markets. The welfare consequences of a climate shock for smallholders depend not only on its direct effect on yields, but on how it reshapes the market power of the intermediaries they depend on – a channel largely absent from existing work, which focuses on direct weather-to-yield effects. Where intermediaries adapt, aggregate productivity can rise even as farmers are left worse off, so the efficiency gains from climate-induced restructuring and its distributional costs are two faces of the same mechanism. This poses a genuine policy trade-off: interventions that prevent exit forgo both the reallocation gains and the within-firm upgrading that reallocation enables, while doing nothing leaves farmers exposed to widening markdowns. In future work, I plan to evaluate policies that target the distributional margin directly while preserving the upgrading that concentration sets in motion.

As climate shocks become more frequent, understanding how they redraw the boundaries of market power, and not only the productivity of the land, becomes central to protecting smallholders who remain at the base of global agricultural supply chains.

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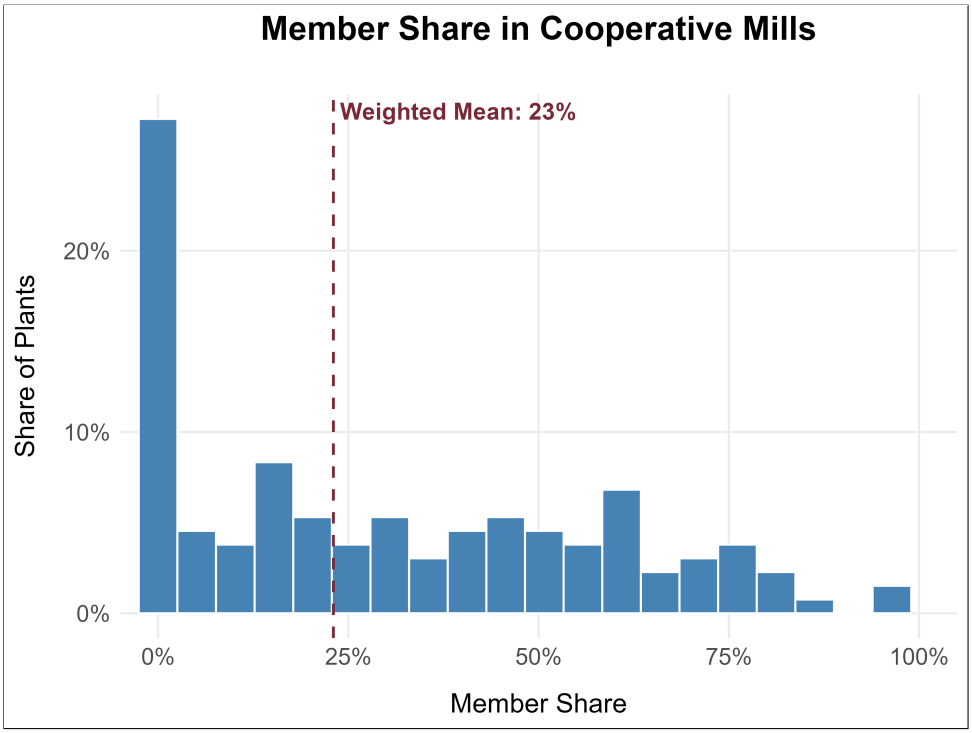
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# Appendix

## A Figures

**Figure A.1:** Share of Members in Cooperative Mills




*Notes:* This figure plots the share of member farmers in cooperative mills across Maharashtra in 2025-26. *Source:* Farmer-Mill Transactions and Plant-level Records from the Maharashtra Sugar Commissionerate.

**Figure A.2:** Industrial Water Requirement

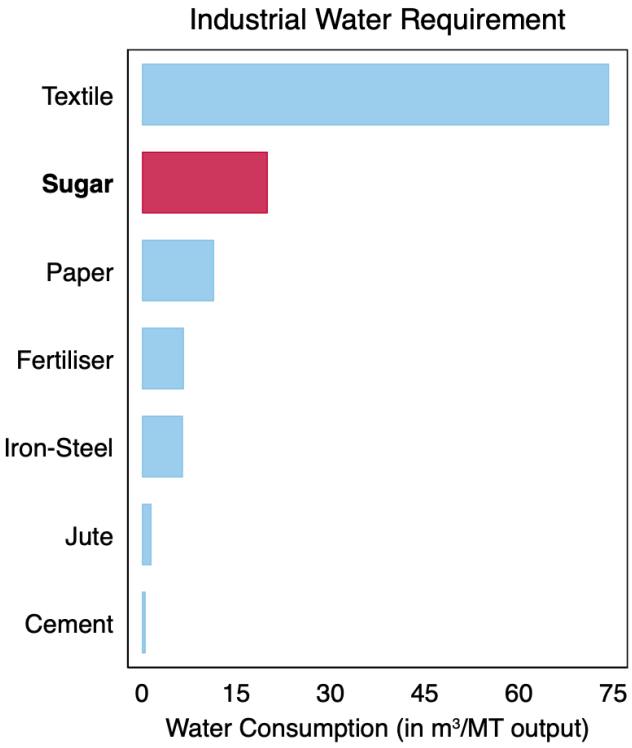
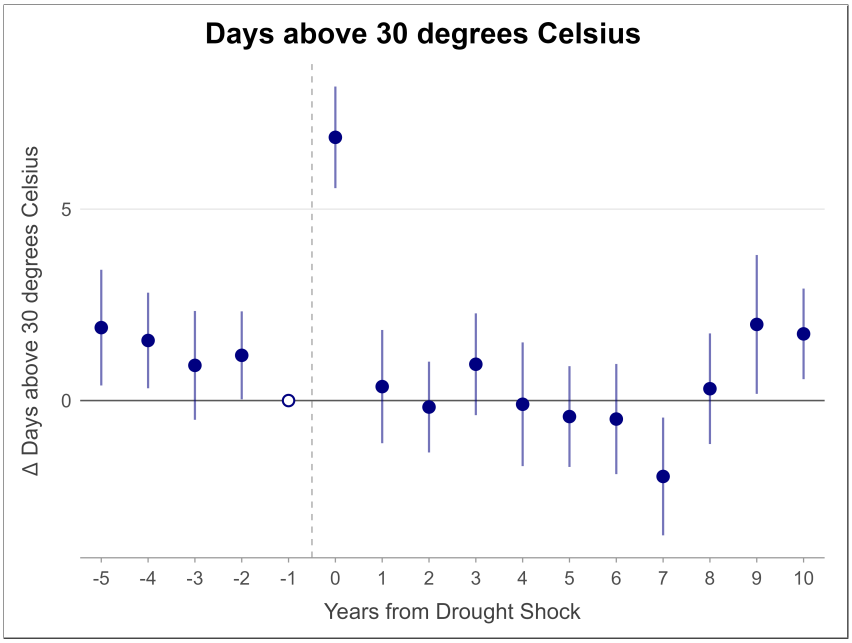



**Figure A.3:** Newspaper Headlines on Drought-induced Mill Closures

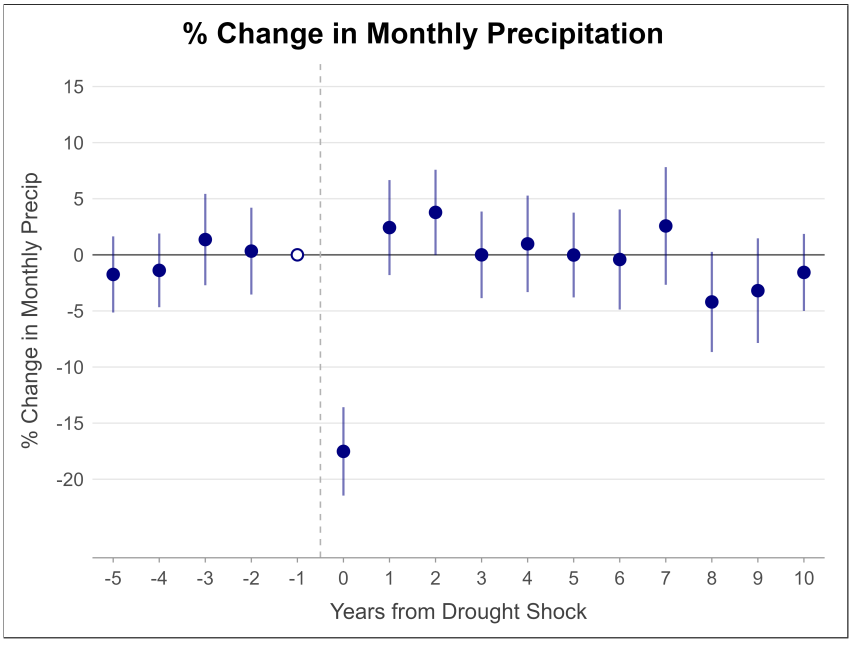


**Figure A.4:** Extreme drought years are considerably hotter and drier than normal

**Panel A:** Exposure to Temperature Above 30 Degrees

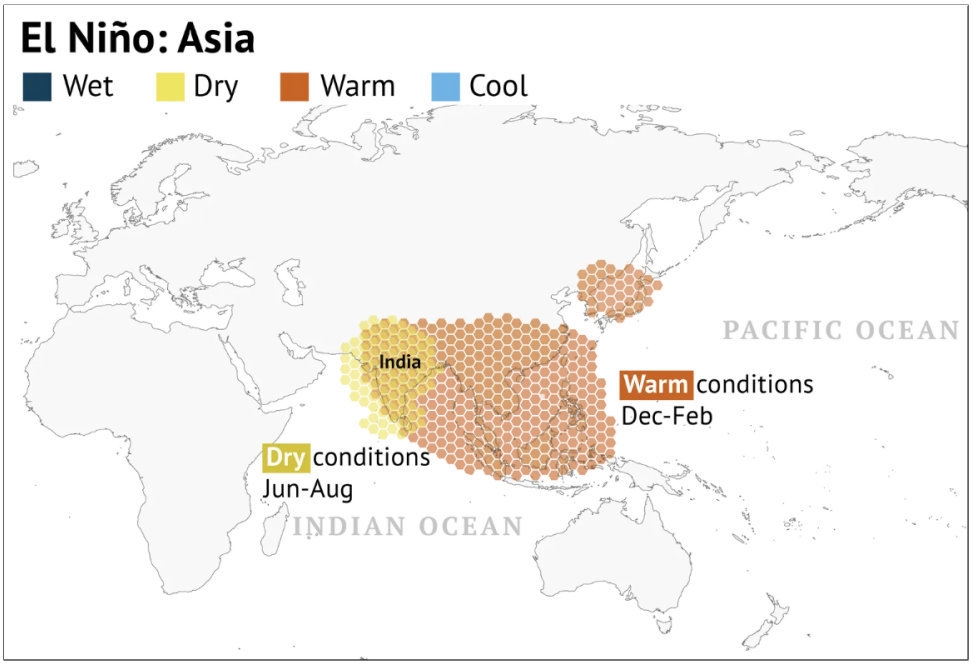



**Panel B:** Monthly Precipitation



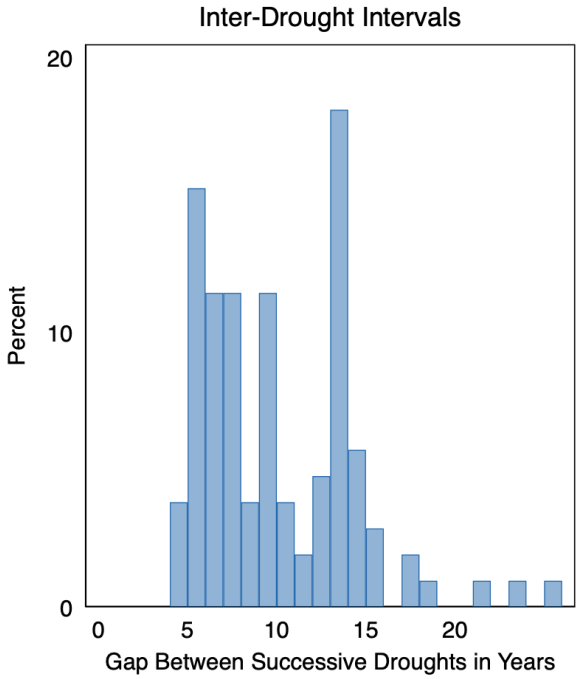

*Notes:* The figure presents event study coefficients from Equation 1 using the Sun and Abraham (2021) estimator on exposure to days with temperature above 30 degrees and precipitation. 95% confidence intervals are computed based on standard errors clustered at the district level.

**Figure A.5:** India falls in El Niño's zone of influence



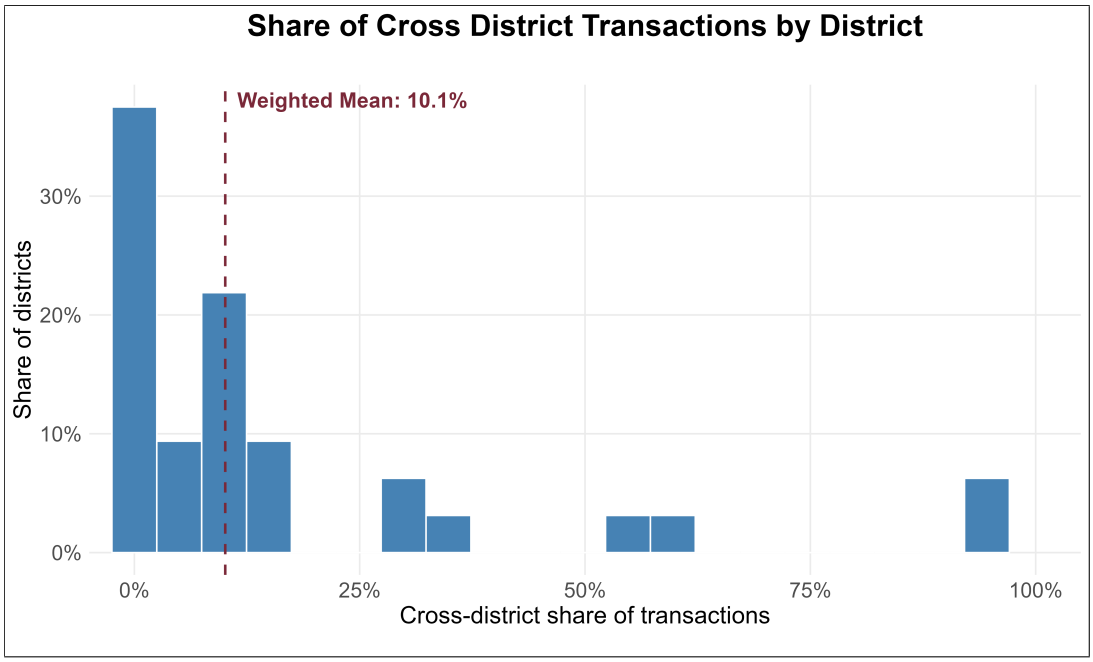

*Notes:* This figure shows how El Niño events create warm conditions during Indian winters and dry conditions during the monsoon, directly impacting cane growth. *Source:* Carbon Brief.

**Figure A.6:** Distribution of time interval between successive droughts




*Notes:* This figure shows yearly intervals between successive droughts within districts that experienced more than one extreme drought from 1990-2025. *Source:* Chuphal et al. (2024).

**Figure A.7:** Share of Cross District Farmer-Mill Transactions



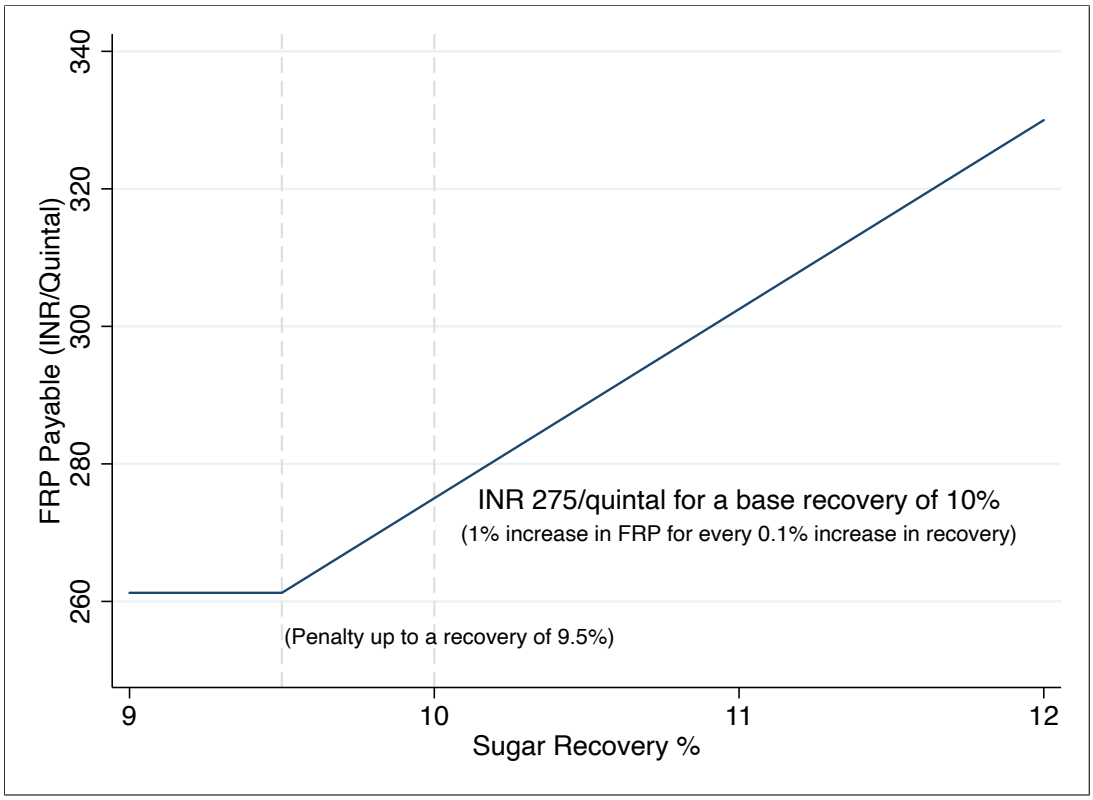

*Notes:* This figure plots the share of farmer-mill transactions that take place across district boundaries. *Source:* Farmer-Mill Transactions and Plant-level Records from the Maharashtra Sugar Commissionerate.

**Figure A.8:** Monthly Sugar Release Allocations

| Sl. No. | Plant Code | Plant Name | Notional Stock as on 31.07.2024 | Quota calculated as per Notional Stock |
|---|---|---|---|---|
| (1) | (2) | (3) | (4) | (5) |
| | **State:** | **Punjab** | | |
| 383 | 101 | GURDASPUR | 11466 | 2371 |
| 384 | 201 | BATALA | 9126 | 1887 |
| 385 | 301 | FAZILKA | 3111 | 643 |
| 386 | 401 | MORINDA | 15514 | 3208 |
| 387 | 501 | BHOGPUR | 17270 | 3571 |

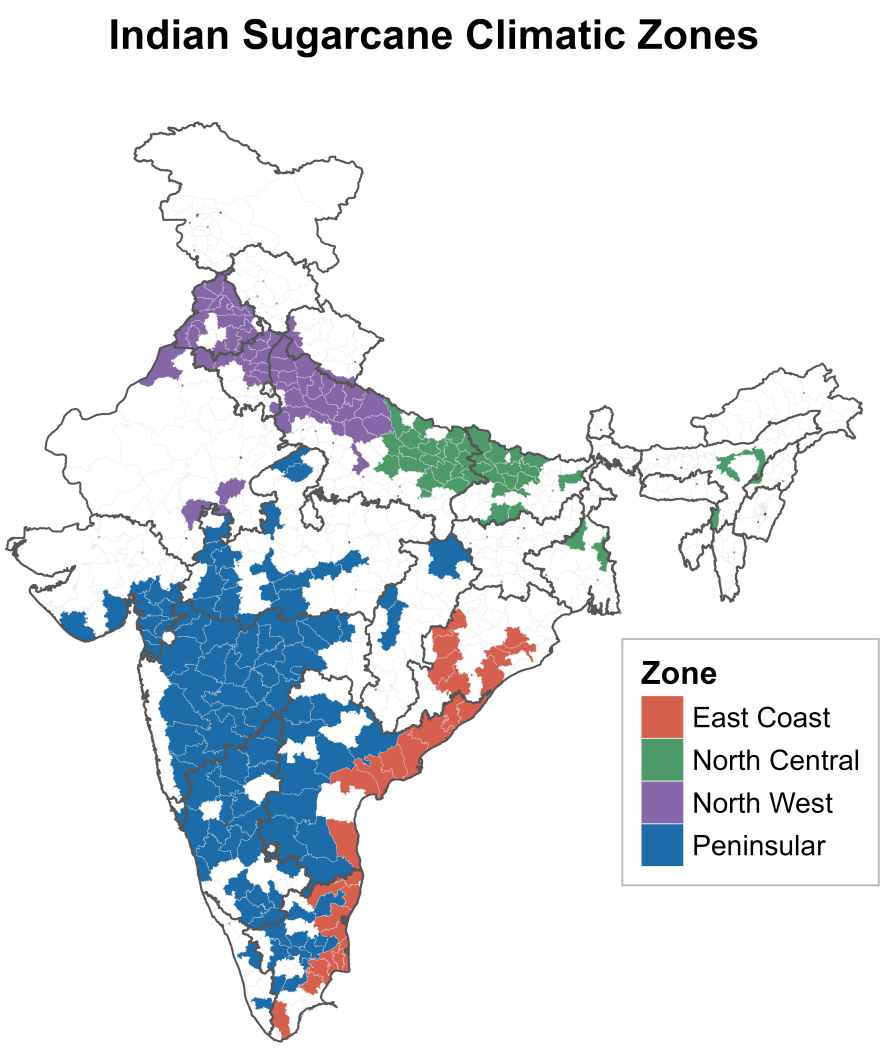
*Notes:* This figure shows monthly sugar release allocations outlined by the Indian Directorate of Sugar for sugar mills in Punjab for August 2024. *Source:* Indian Directorate of Sugar.

**Figure A.9: Cane Price Floor:** Fair and Remunerative Price Schedule in 2018



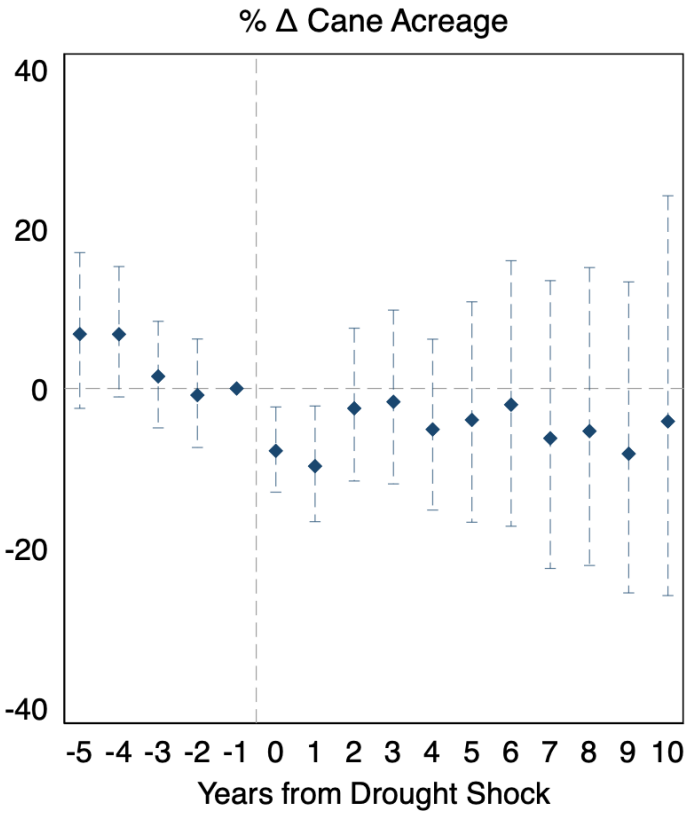

*Notes:* This figure shows the cane price floor schedule, called the Fair and Remunerative Price (FRP), set by the Indian Directorate of Sugar in 2018.

**Figure A.10:** Cane Climatic Zones in India



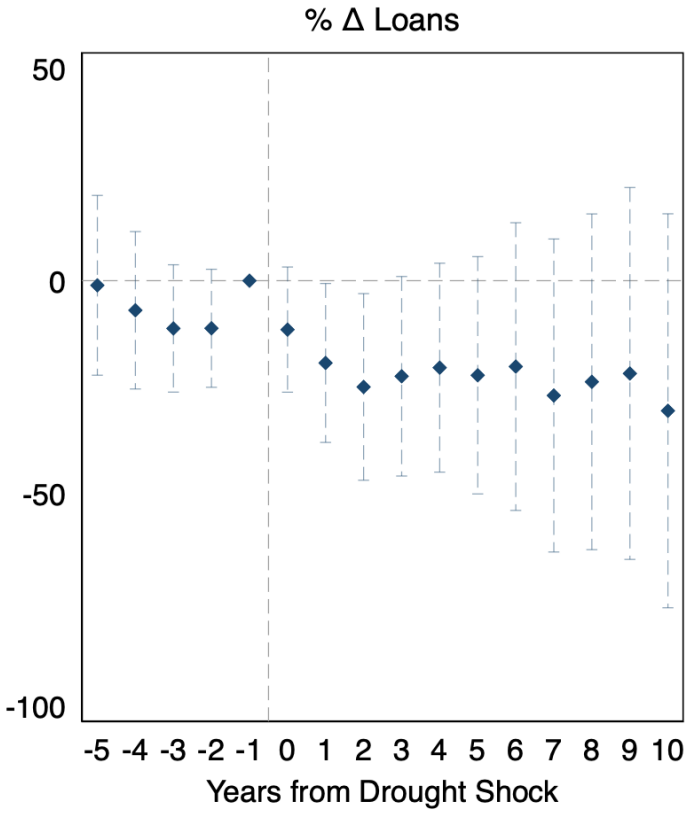

*Notes:* This figure shows the four established cane climatic zones in India based on regional soil types, agro-climatic conditions, sugarcane spread, and historical productivity performance.

**Figure A.11: Effects on Cane Acreage:** Cane acreage falls temporarily in response to droughts




*Notes:* This figure presents event-study coefficients from Equation 1 using the Sun and Abraham (2021) estimator on cane acreage. 95% confidence intervals are computed based on standard errors clustered at the district level. Source: ICRISAT and the Indian Directorate of Economics and Statistics

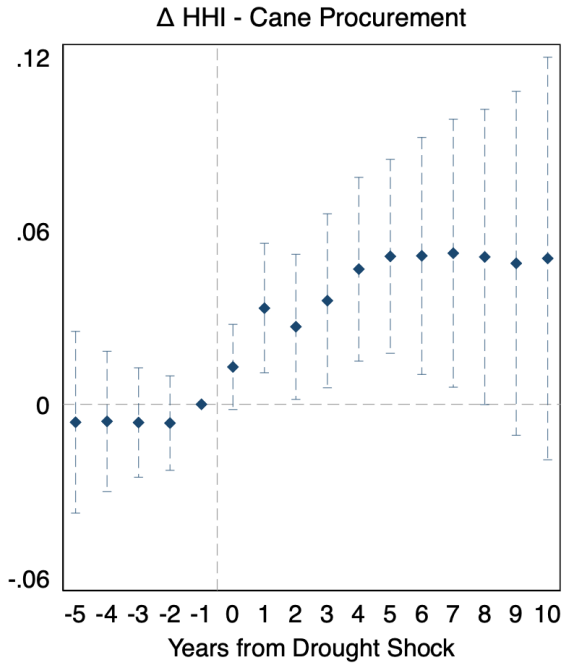
**Figure A.12: Effects on Credit Access:** Credit does not expand to cushion mills during droughts, suggesting credit market frictions



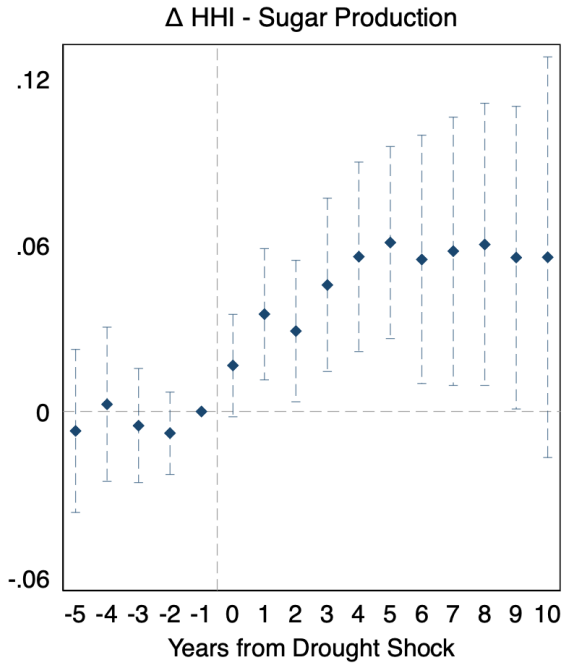

*Notes:* This figure presents event-study coefficients from Equation 1 using the Sun and Abraham (2021) estimator on outstanding loan amounts. 95% confidence intervals are computed based on standard errors clustered at the district level. Source: Plant-level Records from the Annual Survey of Industries.

**Figure A.13: Effects on Market Concentration:** Market concentration sees a persistent rise in drought-hit markets

**Panel A:** HHI - Cane Procurement Shares



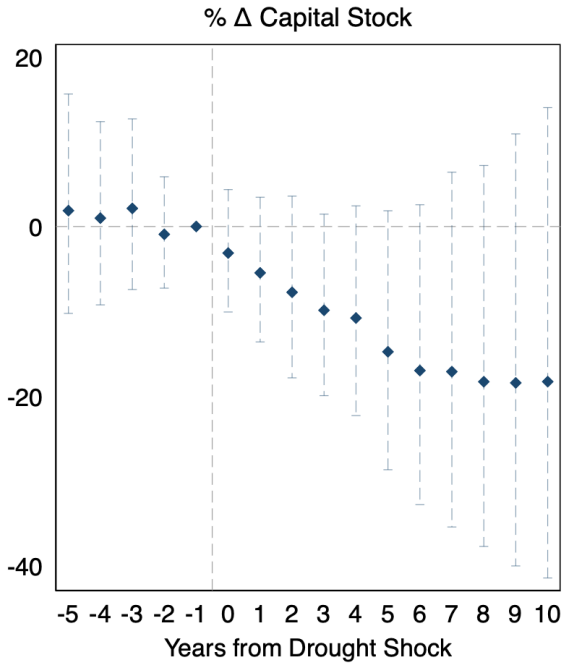

**Panel B:** HHI - Sugar Production Shares



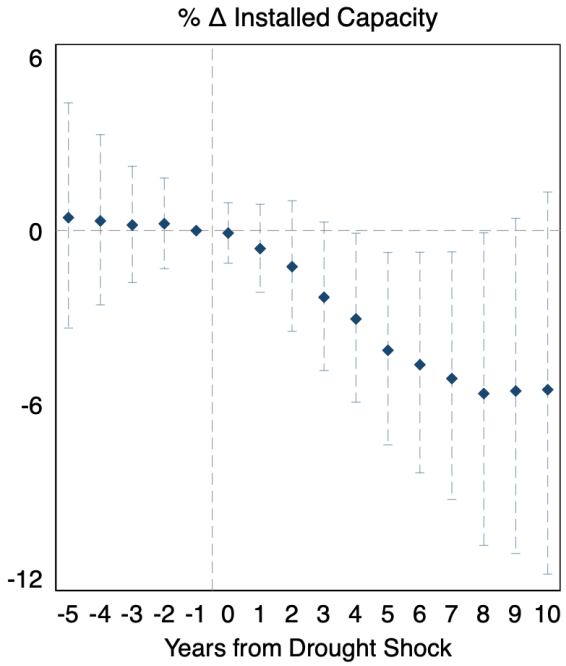

*Notes:* The figure presents event study coefficients from Equation 1 using the Sun and Abraham (2021) estimator. The dependent variables are the Herfindahl-Hirschman Index (HHI) using cane procurement shares in Panel A, and using sugar production shares in Panel B. 95% confidence intervals are computed based on standard errors clustered at the district level. *Source:* Plant-level Records from the Indian Directorate of Sugar.

**Figure A.14: Effects on Capital:** Capital stock falls within drought-hit mills as capacity expansion slows relative to control mills

**Panel A:** Net Capital Stock

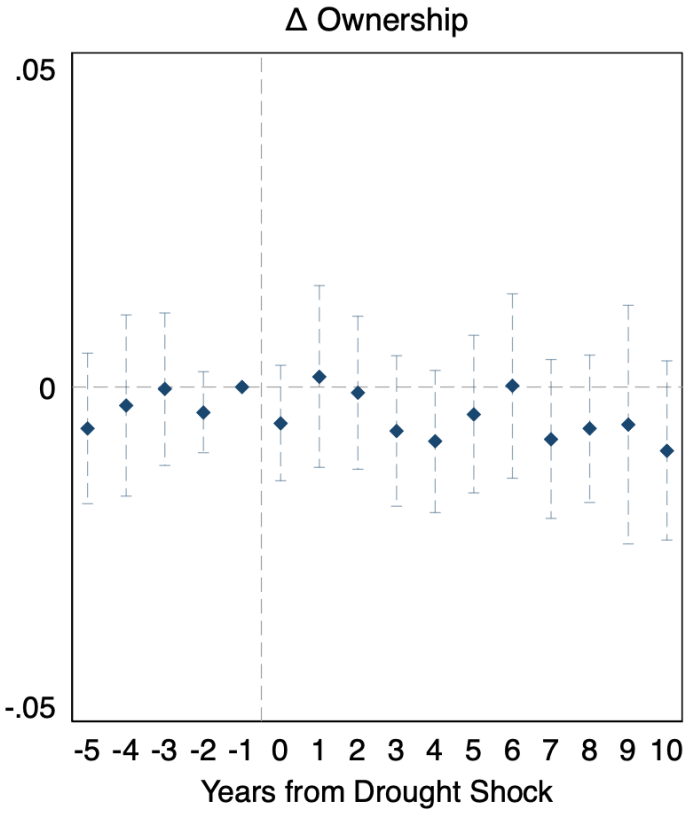



**Panel B:** Installed Capacity



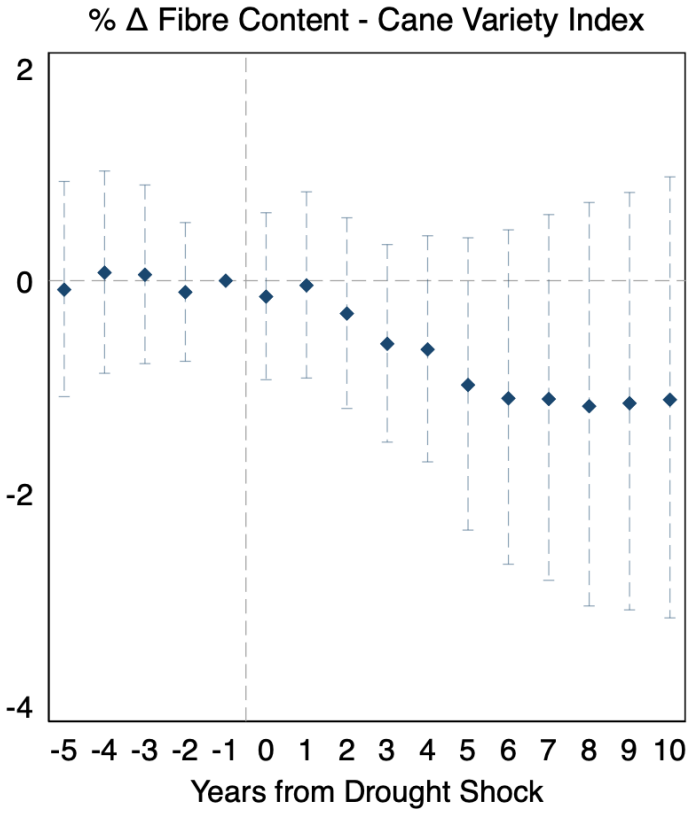

*Notes:* The figure presents event study coefficients from Equation 1 using the Sun and Abraham (2021) estimator. The dependent variables are plant-level net capital stock in Panel A, and installed capacity (in TCD) in Panel B. 95% confidence intervals are computed based on standard errors clustered at the district level. *Source:* Plant-level Records from the Indian Directorate of Sugar and the Annual Survey of Industries.

**Figure A.15: Effects on Ownership:** Mill ownership does not change in response to droughts




*Notes:* This figure presents event-study coefficients from Equation 1 using the Sun and Abraham (2021) estimator on ownership change dummy. 95% confidence intervals are computed based on standard errors clustered at the district level. Source: Plant-level Records from the Indian Directorate of Sugar and the Annual Survey of Industries.

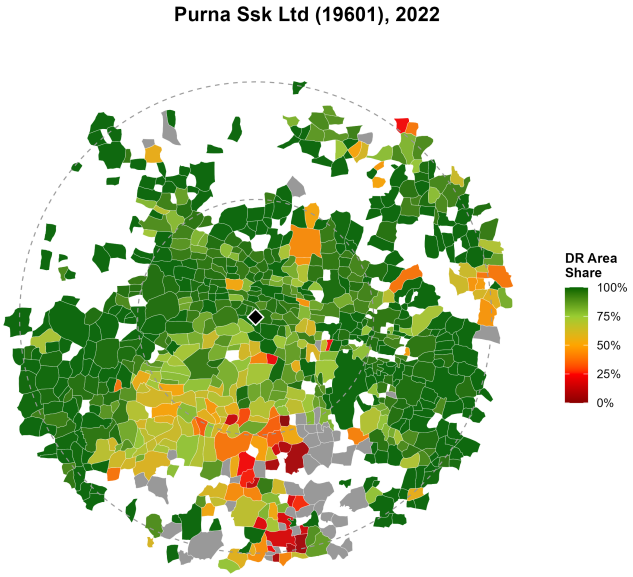
**Figure A.16: Effects on Cane Varieties:** Fibre content in cane for marginal survivors falls, indicating a move towards juicier, sucrose heavy varieties



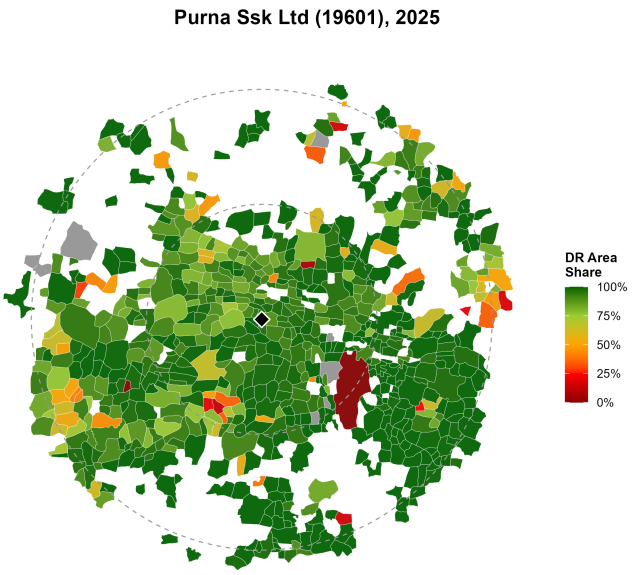

*Notes:* This figure presents event-study coefficients from Equation 1 using the Sun and Abraham (2021) estimator on cane fibre content. 95% confidence intervals are computed based on standard errors clustered at the district level. Source: Plant-level Records from the Indian Directorate of Sugar.

**Figure A.17: Effects on Cane Varieties:** Cultivation of drought-resistant varieties grows in response to droughts.

**Panel A:** Pre Drought



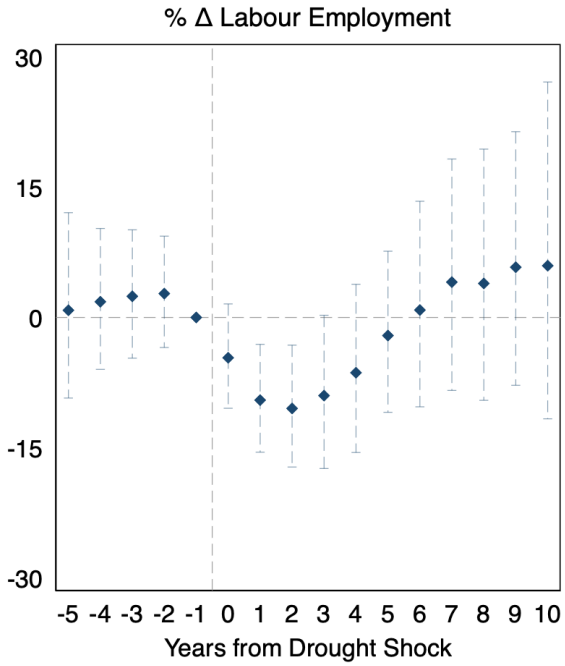

**Panel B:** Post Drought



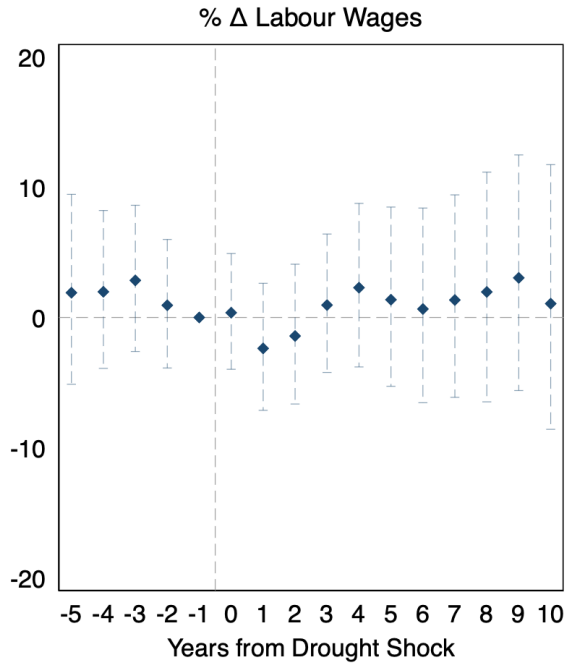

*Notes:* This figure shows village-wise share of drought-resistant varieties grown in the catchment of Purna sugar mill in Maharashtra before and after facing a drought in 2022.

**Figure A.18: Effects on Labour:** Labour employment reduces temporarily in response to droughts, before reaching pre-drought levels but when mills are also operating at higher scale, suggesting improvements in labour productivity. Labour wages see no change, suggestive of competitive labour markets

**Panel A:** Labour Employment

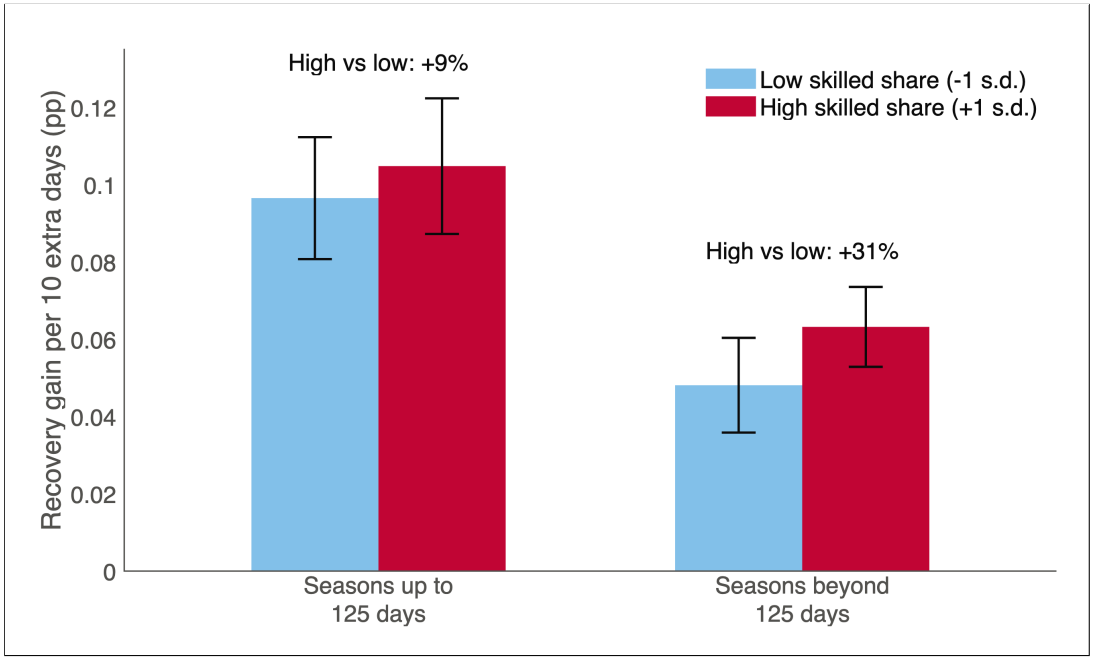



**Panel B:** Labour Wages




*Notes:* This figure presents event-study coefficients from Equation 1 using the Sun and Abraham (2021) estimator on labour employment and wages. 95% confidence intervals are computed based on standard errors clustered at the district level. Source: Plant-level Records from the Annual Survey of Industries.

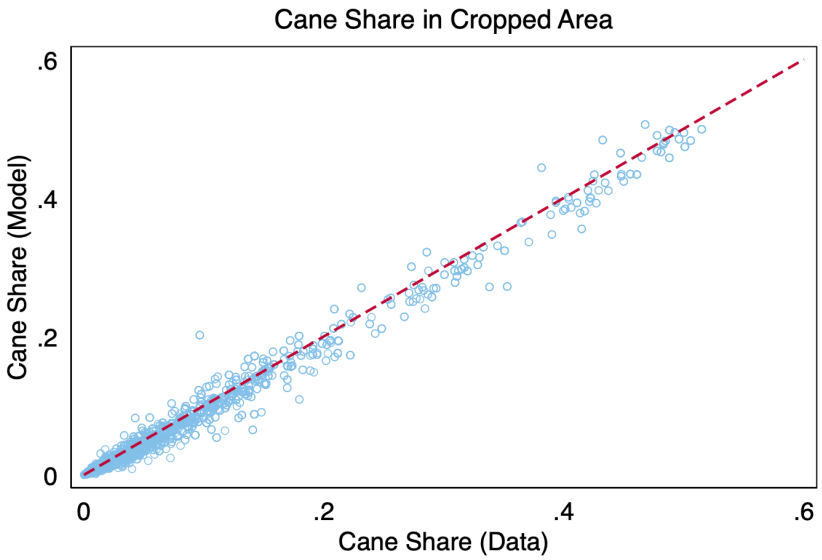
**Figure A.19:** Sugar recovery within mills rises after a 125 day season with an increase in skilled worker share



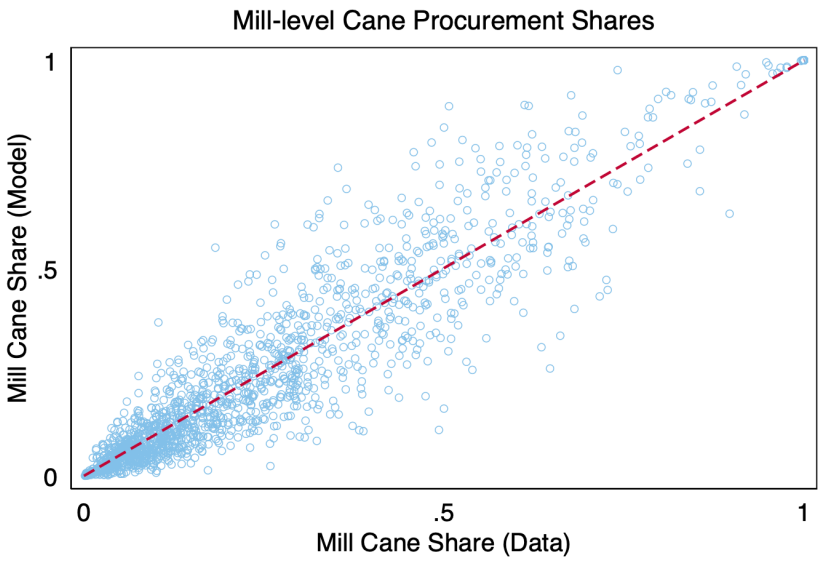

*Notes:* The figure plots the within-mill increase in sugar recovery (percentage points) per 10 extra days of crushing, separately for seasons up to and beyond 125 days, for mills one standard deviation below and above the mean skilled share of the workforce. This is estimated from a regression of sugar recovery on season length and its interaction with the mill-average skilled share, with mill and cane zone-year fixed effects, on working seasons of 45–225 days excluding drought years 0–1 (95% confidence intervals clustered by mill).

**Figure A.20:** Model fit on targeted moments

**Panel A:** Cane Share in Cropped Area




**Panel B:** Mill Cane Shares




*Notes:* This figure shows model fit on two targeted moments: (a) cane share in district cropped area, and (b) mill-level cane procurement shares within a district.

# B Tables

**Table B.1:** Plants' exit likelihood rises after droughts, particularly for the least productive

| | Likelihood of Exit | | |
|---|---|---|---|
| | (1) | (2) | (3) |
| Drought | $0.029^{***}$ | $0.018^{**}$ | $0.126^{***}$ |
| | $(0.007)$ | $(0.007)$ | $(0.038)$ |
| Drought $\times$ **1**{Bottom Tercile of Productivity} | | $0.036^{***}$ | |
| | | $(0.012)$ | |
| Drought $\times$ Lagged Productivity | | | $-0.011^{***}$ |
| | | | $(0.004)$ |
| Mill FE | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes |
| Observations | 5,590 | 5,590 | 5,590 |
| Clusters (Districts) | 203 | 203 | 203 |

*Notes:* This table shows plants' likelihood to shut down permanently within 5 years of the drought. The first column shows the coefficient for all plants in my overall sample, while the second column shows the heterogeneity in exit likelihoods based on whether the plant was in the bottom tercile of productivity distribution right before the drought. The third column uses continuous lagged productivity for heterogeneity. Standard errors clustered at the district level in parentheses. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

**Table B.2:** Frequency of extreme, 1-in-50-year droughts across Indian cane markets

| Frequency | # Districts | Percent |
|---|---|---|
| 0 | 73 | 32 |
| 1 | 57 | 25 |
| 2 | 34 | 15 |
| 3 | 24 | 11 |
| 4 | 25 | 11 |
| 5 | 13 | 6 |
| **Total** | **226** | **100** |

*Source:* Chuphal et al. (2024)

**Table B.3:** Production Function Estimates

| | Ordinary Least Squares | Dynamic Panel | Control Function |
|---|---|---|---|
| $\beta_L$ | 0.775*** | 0.726*** | **0.710*** ** |
| | (0.012) | (0.028) | (0.094) |
| $\beta_K$ | 0.303*** | 0.279*** | **0.323*** ** |
| | (0.004) | (0.008) | (0.028) |
| Scale Parameter | 1.078 | 1.005 | **1.033** |
| Observations | 10,610 | 7,867 | 7,867 |

*Notes:* Standard errors are block-bootstrapped with 200 iterations.

# C Theoretical Appendix

This appendix solves the model of Section 6 in full. Appendix C.1 derives the mill's optimality conditions — the wage condition, the cane markdown, the upgrading threshold, and the cane input-demand function. Appendix C.2 derives the nested discrete-choice supply system — the inner mill shares, the outer crop shares, the inclusive value, the nesting-consistency restriction, and the residual-supply elasticity.

## C.1 The Mill's Problem

### C.1.1 Setup

Mill $i$ in market-year $(d, t)$ produces sugar with the Leontief technology

$$Q_{it} = \min\left\{\beta_{it}^{M} M_{it},\ \Omega_{it} H(L_{it}, K_{it})\right\}. \tag{3}$$

It is never optimal to leave either arm slack: cane in excess of $\Omega_{it} H / \beta_{it}^{M}$ raises cost without raising output, and labour in excess of that implied by $H(L, K) = \beta_{it}^{M} M / \Omega_{it}$ does likewise. Hence both arms bind,

$$Q_{it} = \beta_{it}^{M} M_{it} = \Omega_{it} H(L_{it}, K_{it}), \tag{C.1}$$

and the mill's choice of labour and cane is linked by $H(L_{it}, K_{it}) = \beta_{it}^{M} M_{it} / \Omega_{it}$. I drop the $it$ subscripts within derivations. The mill is a price-taker in sugar ($P^{s}$) and labour ($W^{L}$) and an oligopsonist in cane: it faces an upward-sloping residual supply curve $C_i(W^{M})$ with inverse $W^{M}(M)$, and internalizes that procuring more cane raises the price it must pay. Let

$$\varepsilon^{s} \equiv \frac{d \ln C_i}{d \ln W^{M}} > 0 \tag{C.2}$$

denote the residual-supply elasticity (derived in Appendix C.2). Fixing the upgrading regime, write realised recovery as $\tilde{\beta}^{M} \in \{\beta^{M}, \gamma\beta^{M}\}$. Variable profit, gross of the upgrading and operational cost, is

$$\Pi = P^{s} \tilde{\beta}^{M} M - W^{M}(M)\, M - W^{L} L, \qquad \text{s.t. } H(L, K) = \frac{\tilde{\beta}^{M} M}{\Omega}, \quad M \le \bar{M}. \tag{C.3}$$

### C.1.2 Marginal cost of cane

Because the mill moves along its residual supply curve, the marginal expenditure on cane exceeds the price:

$$\frac{d\left[W^{M}(M)\, M\right]}{dM} = W^{M} + M \frac{dW^{M}}{dM} = W^{M}\left(1 + \frac{d \ln W^{M}}{d \ln M}\right) = W^{M} \frac{\varepsilon^{s} + 1}{\varepsilon^{s}}, \tag{C.4}$$

using $\dfrac{d\ln W^M}{d\ln M} = 1/\varepsilon^s$ from (C.2). The wedge $\frac{\varepsilon^s+1}{\varepsilon^s} > 1$ is the source of the markdown.

### C.1.3 Optimal labour and the wage condition

Substitute $M = \Omega H(L,K)/\tilde{\beta}^M$ from (C.1) into (C.3), so that the mill chooses $L$ (with $M$ following) subject to $M \le \bar{M}$. Form the Lagrangian with multiplier $\lambda \ge 0$ on the capacity constraint $\Omega H(L,K)/\tilde{\beta}^M \le \bar{M}$:

$$\mathcal{L} = P^s \Omega H(L,K) - W^M(M)\, M - W^L L - \lambda\Big(\tfrac{\Omega H(L,K)}{\tilde{\beta}^M} - \bar{M}\Big).$$

Using $\dfrac{dM}{dL} = \dfrac{\Omega H_L}{\tilde{\beta}^M}$ and (C.4), the first-order condition $\partial\mathcal{L}/\partial L = 0$ is

$$P^s \Omega H_L - W^M \frac{\varepsilon^s+1}{\varepsilon^s}\cdot\frac{\Omega H_L}{\tilde{\beta}^M} - W^L - \lambda\frac{\Omega H_L}{\tilde{\beta}^M} = 0,$$

which rearranges to the wage condition

$$W^L = \Omega H_L\left[P^s - \frac{W^M}{\tilde{\beta}^M}\frac{\varepsilon^s+1}{\varepsilon^s} - \frac{\lambda}{\tilde{\beta}^M}\right], \qquad H_L \equiv \frac{\partial H}{\partial L}. \tag{C.5}$$

The wage equals the marginal revenue product of labour, net of the marginal cane expenditure the extra output obliges (inclusive of the oligopsony wedge) and of the capacity shadow value.

### C.1.4 The cane markdown

Equivalently, differentiate (C.3) directly in $M$ (with $L$ following through (C.1), $dL/dM = \tilde{\beta}^M/(\Omega H_L)$). The first-order condition $\partial\mathcal{L}/\partial M = 0$ equates marginal revenue net of marginal labour cost to the marginal cane expenditure and capacity value:

$$P^s\tilde{\beta}^M - W^L\frac{\tilde{\beta}^M}{\Omega H_L} - W^M\frac{\varepsilon^s+1}{\varepsilon^s} = \lambda.$$

Collecting terms and defining the *net* marginal revenue product of cane,

$$\mathrm{NetMRP}^M \equiv \tilde{\beta}^M\Big(P^s - \frac{W^L}{\Omega H_L}\Big), \tag{C.6}$$

gives

$$W^M\frac{\varepsilon^s+1}{\varepsilon^s} = \mathrm{NetMRP}^M - \lambda \quad\Longrightarrow\quad \boxed{W^M = \frac{\varepsilon^s}{\varepsilon^s+1}\big(\mathrm{NetMRP}^M - \lambda\big).} \tag{8}$$

This is the markdown in the main text. The factor $\frac{\varepsilon^s}{\varepsilon^s+1} < 1$ marks the cane price below its marginal value product; a less elastic residual supply (lower $\varepsilon^s$) deepens the markdown, and a binding capacity constraint ($\lambda > 0$) lowers the offered price further. The wage condition (C.5) and the markdown (8) are the same optimum written in the two choice variables: multiplying (8)'s predecessor by $\Omega H_L / \tilde{\beta}^M$ returns (C.5). When the floor binds the mill instead pays $W^M = \phi_0 + \phi_1(\tilde{\beta}^M - \bar{\beta}^M)$.

### C.1.5 The upgrading decision

Upgrading is the discrete choice $u \in \{0, 1\}$. Let $\widetilde{\Pi}(u)$ be the mill's optimized variable profit (C.3) under regime $u$; the mill upgrades iff

$$\widetilde{\Pi}(1) - \widetilde{\Pi}(0) \;\geq\; F_{\text{up}}. \tag{C.7}$$

Evaluate both regimes at a common scale $M$ and a slack floor, and write the slack-floor markdown compactly as $W^M = \psi\, P^s \tilde{\beta}^M$ with $\psi \equiv \frac{\varepsilon^s}{\varepsilon^s+1}$. Then revenue net of cane expenditure in regime $u$ is

$$P^s \tilde{\beta}^M(u)\, M - W^M M = \big(1 - \psi\big) P^s \tilde{\beta}^M(u)\, M,$$

and the labour and operating terms are common across regimes and cancel. Substituting $\tilde{\beta}^M(1) = \gamma \beta^M$ and $\tilde{\beta}^M(0) = \beta^M$ into (C.7),

$$(1-\psi) P^s \gamma \beta^M M - (1-\psi) P^s \beta^M M \;\geq\; F_{\text{up}},$$

which rearranges to the upgrading condition and its implied scale threshold,

$$(1-\psi)\, P^s (\gamma - 1) \beta^M M \;\geq\; F_{\text{up}} \quad\Longleftrightarrow\quad M \;\geq\; M^* \equiv \frac{F_{\text{up}}}{(1-\psi)\, P^s (\gamma - 1) \beta^M}. \tag{9}$$

Two comparative statics follow directly. (i) *Scale–upgrading complementarity.* The left side of (9) is increasing in $M$, so only mills above $M^*$ upgrade; reallocation that raises a survivor's scale pushes it past the threshold. (ii) *Buyer power.* Since $1 - \psi = \frac{1}{\varepsilon^s+1}$ is larger when residual supply is less elastic, greater buyer power lowers $M^*$: the mill retains a larger share $(1 - \psi)$ of the upgrading surplus, the remainder $\psi$ accruing to farmers through the higher cane price $W^M = \psi P^s \tilde{\beta}^M$ that upgrading induces.

### C.1.6 Cane input demand

Let the labour–capital aggregate be Cobb–Douglas, $H(L, K) = L^{\beta^L} K^{\beta^K}$, so $H_L = \beta^L L^{\beta^L - 1} K^{\beta^K}$. Under a slack floor and slack capacity ($\lambda = 0$), the wage condition

(C.5) reads

$$W^L = \Omega\,\beta^L L^{\beta^L-1} K^{\beta^K} \underbrace{\left[P^s - \frac{W^M}{\tilde{\beta}^M}\frac{\varepsilon^s+1}{\varepsilon^s}\right]}_{\equiv\mathcal{A}}.$$

Solving for optimal labour,

$$L^{1-\beta^L} = \frac{\Omega\,\beta^L K^{\beta^K}\mathcal{A}}{W^L} \quad\Longrightarrow\quad L = \left(\frac{\Omega\,\beta^L K^{\beta^K}\mathcal{A}}{W^L}\right)^{\frac{1}{1-\beta^L}}.$$

Substituting into the binding Leontief identity $M = \Omega H(L,K)/\tilde{\beta}^M = \Omega L^{\beta^L} K^{\beta^K}/\tilde{\beta}^M$ and collecting exponents (the exponent on $\Omega$ is $1 + \frac{\beta^L}{1-\beta^L} = \frac{1}{1-\beta^L}$, and on $K$ is $\beta^K + \frac{\beta^K\beta^L}{1-\beta^L} = \frac{\beta^K}{1-\beta^L}$) yields the cane input-demand function

$$M^* = \frac{1}{\tilde{\beta}^M}\left(\Omega\,(\beta^L)^{\beta^L} K^{\beta^K}\left[\frac{P^s - \frac{W^M}{\tilde{\beta}^M}\left(\frac{\varepsilon^s+1}{\varepsilon^s}\right)}{W^L}\right]^{\beta^L}\right)^{\frac{1}{1-\beta^L}}. \tag{10}$$

Compactly $M = m\big(P^s, W^M, W^L, K, \beta^L, \beta^K, \tilde{\beta}^M, \Omega, \varepsilon^s\big)$, which is strictly increasing in $\Omega$. Since every argument except $(\beta^L, \beta^K, \Omega)$ is observed (with $\varepsilon^s$ supplied by the supply model), monotonicity in $\Omega$ makes (10) the proxy that inverts for latent productivity in estimation.

## C.2 The Nested Discrete-Choice Supply Model

A market $d$ contains a unit mass of plots $\omega$ with cultivable area $\bar{L}_d$. Each plot is allocated to the crop, and conditional on cane the mill, yielding the highest revenue per hectare. At the outer level the plot goes to one of $K+1$ crops $k \in \{0,1,\ldots,K\}$ ($k=0$ is cane); at the inner level, conditional on cane, to a mill $i \in \mathcal{I}_d \cup \{0\}$ ($\{0\}$ the jaggery outside option). For a competing crop $k \geq 1$, $R_k(\omega) = \tilde{p}_k\,\eta_k(\omega)$; for cane to mill $i$, $R_{0i}(\omega) = P_i\,\eta_0(\omega)\,\nu_i(\omega)$, with

$$\ln P_i = \tfrac{1}{\theta}\delta_i, \qquad \delta_i = \alpha \ln W_i^M + x_{it}'\gamma + \xi_i, \qquad \delta_0 \equiv 0. \tag{11}$$

### C.2.1 Outer nest: Fréchet crop shares

Crop productivities are independent Fréchet, $\Pr[\eta_k \leq \eta] = \exp(-T_k\eta^{-\theta})$, $\theta > 1$. For crop $k$, revenue $R_k = \tilde{p}_k\eta_k$ inherits a Fréchet law,

$$\Pr[R_k \leq r] = \Pr\big[\eta_k \leq r/\tilde{p}_k\big] = \exp\big(-T_k\tilde{p}_k^{\theta}\,r^{-\theta}\big),$$

i.e. Fréchet with scale $S_k \equiv T_k \tilde{p}_k^{\theta}$. The maximum of independent Fréchet variates is Fréchet with scale $\sum_k S_k$, and plot $\omega$ is allocated to crop $k$ with probability $S_k / \sum_{k'} S_{k'}$:

$$s_k(d,t) = \frac{T_k \, \tilde{p}_k^{\theta}}{\sum_{k'} T_{k'} \, \tilde{p}_{k'}^{\theta}}. \tag{14}$$

This also gives the elementary comparative static used below, $\dfrac{d \ln s_k}{d \ln \tilde{p}_k} = \theta(1 - s_k)$.

### C.2.2 Inner nest: logit mill shares and the inclusive value

Conditional on cane, the common component $\eta_0(\omega)$ cancels from the comparison across mills, so the choice depends on $P_i \nu_i$. With i.i.d. Gumbel mill shocks at scale $\sigma$, revenue maximization in levels is additive random-utility maximization in logs, and the conditional mill share is multinomial logit in $\delta_i$ at scale $\sigma$:

$$s_{i|0}(d,t) = \frac{\exp(\delta_i/\sigma)}{\sum_{i' \in \mathcal{I}_d \cup \{0\}} \exp(\delta_{i'}/\sigma)}. \tag{12}$$

The expected payoff from the best mill option is the inclusive value

$$IV_0(d,t) = \sigma \ln \sum_{i \in \mathcal{I}_d \cup \{0\}} \exp(\delta_i/\sigma). \tag{13}$$

Two derivatives recur below:

$$\frac{\partial \, IV_0}{\partial \delta_i} = s_{i|0}, \qquad \frac{\partial \ln s_{i|0}}{\partial \delta_i} = \frac{1}{\sigma}\big(1 - s_{i|0}\big). \tag{C.8}$$

### C.2.3 The cane effective price and nesting consistency

The cane nest enters the outer problem through an effective price that aggregates the mill options,

$$\tilde{p}_0(d,t) = \exp\big(IV_0(d,t)/\alpha\big). \tag{C.9}$$

Substituting (C.9) and (13) into (14) with $k = 0$, the cane nest contributes to the outer denominator the term

$$T_0 \, \tilde{p}_0^{\theta} = T_0 \exp\Big(\tfrac{\theta}{\alpha} IV_0\Big) = T_0 \Big[\sum_{i \in \mathcal{I}_d \cup \{0\}} \exp(\delta_i/\sigma)\Big]^{\theta\sigma/\alpha}.$$

A valid two-level nested-GEV generator (McFadden, 1977) aggregates the inner alternatives as $\big(\sum_i \exp(\delta_i/\sigma)\big)^{\rho_0}$, where $\rho_0 \in (0,1]$ is the cane-nest dissimilarity parameter.

Matching exponents identifies

$$\boxed{\rho_0 = \frac{\theta\sigma}{\alpha} \in (0,1] \quad \Longleftrightarrow \quad \frac{\alpha}{\sigma} \geq \theta.} \tag{16}$$

Economically, mills must be closer substitutes for one another than cane is for competing crops: the within-cane elasticity $\alpha/\sigma$ weakly exceeds the across-crop elasticity $\theta$. The restriction is not imposed; $\alpha/\sigma$ and $\theta$ are estimated separately, and (16) is an over-identifying test of the nesting structure.

### C.2.4 Residual supply and its elasticity

Cane delivered to mill $i$ is land times yield times the two shares,

$$C_i(d,t) = \bar{L}_d \, y_0(d,t) \, s_0(d,t) \, s_{i|0}(d,t). \tag{15}$$

Only the two shares depend on $W_i^M$, and through (11) $\partial\delta_i/\partial \ln W_i^M = \alpha$. Hence

$$\varepsilon_i^s = \frac{d \ln C_i}{d \ln W_i^M} = \underbrace{\frac{\partial \ln s_{i|0}}{\partial \ln W_i^M}}_{\text{inner}} + \underbrace{\frac{\partial \ln s_0}{\partial \ln W_i^M}}_{\text{outer}}.$$

For the inner term, (C.8) gives $\dfrac{\partial \ln s_{i|0}}{\partial \ln W_i^M} = \dfrac{1}{\sigma}(1 - s_{i|0}) \cdot \alpha = \dfrac{\alpha}{\sigma}(1 - s_{i|0})$. For the outer term, chain through $\tilde{p}_0$:

$$\frac{\partial \ln s_0}{\partial \ln W_i^M} = \underbrace{\frac{d \ln s_0}{d \ln \tilde{p}_0}}_{\theta(1-s_0)} \cdot \underbrace{\frac{\partial \ln \tilde{p}_0}{\partial \ln W_i^M}}_{(1/\alpha)\, s_{i|0}\, \alpha = s_{i|0}} = \theta \, s_{i|0}(1 - s_0),$$

using (C.9) and (C.8). Adding the two margins gives the residual-supply elasticity,

$$\varepsilon_i^s = \underbrace{\frac{\alpha}{\sigma}\left(1 - s_{i|0}\right)}_{\text{within-cane: steal from rival mills}} + \underbrace{\theta \, s_{i|0}\left(1 - s_0\right)}_{\text{cross-crop: pull land into cane}}. \tag{17}$$

The mechanism of the paper follows from the within-cane margin: when rivals exit, $s_{i|0}$ rises mechanically, lowering $\varepsilon_i^s$ and, through the markdown (8), widening the surviving mill's oligopsony wedge.