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When the rains fail: Climate shocks and firm productivity in Ethiopia

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When the Rains Fail: Climate Shocks and Firm Productivity in Ethiopia

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Abstract

How do climate shocks propagate beyond agriculture and affect industrial productivity in low-income economies? Using panel data from Ethiopia's Large and Medium Manufacturing Industry Survey (2008–2018) matched with drought exposure measures from the Standardised Precipitation Evapotranspiration Index (SPEI), we estimate the impact of climate shocks on manufacturing firms' Total Factor Productivity (TFP). Exploiting the 2011 La Niña drought and the 2016 El Niño event, we implement the Callaway and Sant'Anna (2021) staggered difference-in-differences estimator with doubly-robust inverse probability weighting and TFP estimated following Levinsohn and Petrin (2003). We document three key findings: (i) drought reduces firm TFP by 2–3.5 percent, with effects emerging gradually and persisting over time; (ii) non-agri-dependent firms respond earlier, primarily through demand and financial channels, while agri-dependent firms exhibit delayed effects consistent with slower supply-chain transmission; and (iii) repeated drought exposure amplifies productivity losses non-linearly, with the 2016 drought generating larger and more persistent effects than the 2011 episode. In terms of mechanism, drought-induced labour-productivity disruptions and raw-material shortages are the primary transmission channels, compounded by declining rural demand and limited firm adjustment capacity. Our findings provide the first firm-level evidence that climate shocks impose substantial and persistent productivity costs on manufacturing firms in Sub-Saharan Africa and highlight the importance of resilience-oriented industrial policies.

Keywords: Drought; TFP; Ethiopia; staggered DiD; climate adaptation.

JEL Codes: O13, O14, Q54, L60, C23.

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1. Introduction

Climate change is rapidly becoming one of the most significant constraints on economic development in Sub-Saharan Africa. The region is disproportionately exposed to extreme weather events, and droughts in particular have intensified in frequency and severity over the past half-century (Appendix Figure A2; IPCC 2021). The economic consequences of this exposure are well-documented at the macroeconomic level: Dell et al. (2012) find that higher temperatures reduce GDP growth rates with effects concentrated in poor countries, while Hsiang (2016) conclude that macroeconomic costs in developing countries substantially exceed earlier estimates. In agriculture, the effects of drought are well-characterised (Schlenker and Lobell 2010; Thornton et al. 2014). Yet the question of how climate shocks propagate through the *non*-agricultural economy — and manufacturing in particular — remains almost entirely unanswered at the firm level. This matters because manufacturing-led structural transformation is the centrepiece of the development strategies of Ethiopia, Kenya, Rwanda, and most of their Sub-Saharan African peers. If droughts persistently undermine manufacturing Total Factor Productivity, the productivity upgrading on which these strategies depend is directly and systematically threatened.

The existing firm-level literature on climate shocks has concentrated on floods in advanced economies. Leiter et al. (2009) find creative destruction effects on European firms; Coelli and Manasse (2014) document persistent negative effects on Italian manufacturing. Outside Europe, Zhou and Botzen (2021) find disaster impacts on firm growth in Vietnam, and Traore and Foltz (2018) examine temperature effects on African manufacturing using aggregate data. No existing study provides firm-level causal evidence on the effect of *drought* on manufacturing productivity in a developing-country context. This paper fills that gap.

We do so using Ethiopia, which offers an empirically exceptional setting for three reasons. First, it is Africa's fastest-growing and second-most populous economy, with manufacturing placed explicitly at the centre of its structural transformation agenda through successive Growth and Transformation Plans. Second, it has experienced two large, distinct, and well-documented drought episodes during our sample period, the 2011 La Niña drought affecting 4.8 million people, and the 2016 El Niño event, one of the three strongest since 1950, affecting 10.2 million and generating economic losses equivalent to 2.1 %of GDP. Third, and uniquely, over 87 percent of Ethiopia's electricity is hydropower-generated, creating a direct and observable mechanical link from drought to manufacturing through power outages (Abdisa 2018) — a channel that is unusually clean to identify and that has no counterpart in more energy-diversified economies.

Credible identification in this setting requires solving two methodological challenges simultaneously. The first is the production-function estimation problem. Standard revenue-based TFP conflates physical productivity with market power and output prices: a drought that raises input costs and is partly passed through to output prices will mechanically alter revenue-TFP even if nothing has changed in the physical production process (De Loecker 2011; Foster et al. 2008). We address this by estimating TFP using the Levinsohn and Petrin (2003) control-function approach, following the Fiorini et al. (2021) implementation designed specifically for low-income manufacturing data, with sector-specific elasticities, the Ackerberg et al. (2015) functional-dependence correction, and sector-specific deflation. The result approximates physical productivity and is robust to drought-induced price changes.

The second challenge is identification of the causal effect. Our sample contains two drought episodes that affected overlapping but non-identical sets of firms at different points in time, generating a staggered treatment structure. The conventional two-way fixed effects (TWFE) estimator is biased under staggered adoption with heterogeneous treatment effects (Baker et al. 2022; de Chaisemartin and D'Haultfœuille 2020; Goodman-Bacon 2021), and the bias is particularly severe here because the two droughts differ in severity and duration, and because drought effects are persistent, making already-treated firms a poor counterfactual for later-treated units. We implement the Callaway and Sant'Anna (2021) staggered difference-in-differences estimator, which restricts comparisons to clean control groups and aggregates group-time average treatment effects on the treated (ATTs) in a manner robust to arbitrary treatment-effect heterogeneity. We adopt the doubly-robust inverse probability weighting (DRIPW) variant, which is consistent if either the propensity-score model or the outcome regression is correctly specified.

Our empirical findings are consistent across all specifications. Drought causes a significant, lagged, and persistent decline in firms' TFP. The effect is not contemporaneous but emerges with a lag of one to two years, deepening as firms exhaust their short-term operational buffers — a pattern fundamentally inconsistent with the temporary output disruptions that standard disaster-impact assessments measure, and one that implies a substantial underestimation of the true productivity cost of drought in the existing literature. The overall ATT implies a TFP reduction of approximately 2–3.5 %relative to the counterfactual, with the 2016 El Niño-linked episode generating larger and less-reversible effects than the 2011 episode, consistent with its greater severity and more damaging electricity disruption.

Decomposing the transmission mechanism reveals that labour productivity and raw-material supply disruptions are the primary channels, while a demand contraction arising from the collapse of rural household incomes provides a secondary mechanism.

Capital is strikingly immobile throughout the event window: firms neither disinvest nor upgrade capital in response to the shock, reflecting the binding credit constraints documented in the survey evidence. This immobility is not a passive result but an active driver of persistent TFP losses, since firms are unable to reconfigure their factor mix optimally and instead absorb all adjustment through variable inputs, generating lasting inefficiency from the resulting suboptimal factor combinations.

Three further sets of results extend the baseline findings. The dose-response analysis reveals a monotone, statistically robust relationship between drought severity and TFP loss: firms in the top SPEI tercile suffer losses approximately three times larger than those in the bottom tercile, providing causal validation of the main result and demonstrating that standard binary drought indicators understate the heterogeneity of impact. The analysis of twice-treated firms (those exposed to both the 2011 and 2016 droughts) reveals that repeated drought exposure generates super-additive productivity losses exceeding the sum of the individual-episode effects, consistent with a compounding mechanism in which the second shock finds firms with depleted buffers and eroded supplier relationships (see, e.g., Leiter et al. 2009).

Moreover, agri-dependent and non-agri-dependent firms respond at different event-time horizons. Non-agri-dependent firms show significant TFP losses at $t = +1$, consistent with the fast transmission of demand contraction and financial tightening. Agri-dependent firms show no significant effect at $t = +1$ but large, significant, and deepening TFP losses from $t = +2$ onward, consistent with the structural two-period lag in agricultural supply chains as inventory buffers are exhausted and supplier-base damage accumulates. This timing asymmetry constitutes non-parametric evidence that the two groups face fundamentally different transmission mechanisms — a result that has direct implications for the design and timing of policy responses.

The survey evidence from 1,659 firms provides direct external validity for the econometric findings. Firms most commonly report reduced production capacity (38%) and increased production costs (35%) as the principal effects of drought, with demand contraction (22%) and inventory losses (18%) following closely. The ranking of disruption types closely mirrors the ordering of transmission-channel ATTs estimated in the regression analysis. Critically, the survey reveals that firms do not fail to invest in climate-resilient capital because returns are insufficient; rather, 67 % cite lack of credit access as the primary barrier. This distinction has fundamental policy implications: the observed productivity losses reflect a market failure rather than an efficient equilibrium, implying that targeted financial interventions could generate welfare improvements by enabling resilience investment that firms themselves recognise as beneficial.

These findings carry direct and specific policy implications. Climate risk must be integrated into Ethiopia's industrial development strategy; the concentration of manufacturing activity in agriculture-linked sectors creates systemic vulnerability that will deepen as droughts intensify with climate change. Financial instruments targeting climate adaptation — subsidised credit, drought risk insurance, liquidity support — are needed to overcome the credit-market failures that prevent firms from building resilience. More broadly, our findings reframe climate risk as an industrial policy issue for Sub-Saharan Africa: international climate finance, which has concentrated on agriculture and social protection, should expand its remit to encompass manufacturing-sector resilience as a core component of climate-adaptive development strategy.

This paper makes four distinct contributions. *First*, it provides the first firm-level causal estimates of drought's impact on manufacturing TFP in Sub-Saharan Africa, filling a critical gap in a literature dominated by aggregate cross-country analyses and agricultural applications. *Second*, we implement the Callaway and Sant'Anna 2021 estimator to produce unbiased ATTs under treatment-effect heterogeneity — a contribution to an empirical literature that has too often relied on TWFE specifications that may be severely biased in multi-period, multi-cohort settings. *Third*, we provide a systematic decomposition of the transmission mechanism, estimating the causal drought effect across eight categories of intermediate outcomes — value added, sales, labour productivity, employment, raw materials, production, and capital — and tracing the pathway from drought exposure to TFP reduction with a degree of precision not previously achieved in the natural-disaster literature. *Fourth*, we supplement the econometric analysis with novel primary survey evidence from 1,659 Ethiopian manufacturing firms that reveals the prevalence of disruption, the nature of coping strategies, and the credit-market failures that prevent more effective structural adaptation.

More broadly, the paper reframes drought risk as an industrial policy issue. In economies where manufacturing draws on agricultural inputs, serves rural households, and depends on hydropower, the assumption that manufacturing is relatively insulated from climate shocks is incorrect. If these structural features persist as climate change intensifies, the manufacturing-led structural transformation agendas of Ethiopia and its peers will face an increasingly binding climate constraint that infrastructure investment and credit-market deepening must address if the agenda is to remain viable.

The remainder of the paper is organised as follows. Section 2 presents the Ethiopian context, data, and TFP estimation. Section 3 sets out the empirical strategy. Section 4 presents the baseline results and transmission mechanisms. Section 5 reports the heterogeneity analysis and robustness checks. Section 6 describes the survey evidence and discussion. Section 7 concludes.

2. Context, Data, and TFP Identification

2.1 Institutional Context and Climate Vulnerability

Ethiopia's industrial development strategy has placed manufacturing at the centre of its structural transformation agenda. Successive Growth and Transformation Plans (GTP I, 2010–2015; GTP II, 2015–2020) and the more recent Ten-Year Development Plan (2021–2030) have targeted manufacturing as the principal driver of employment generation, productivity upgrading, and export diversification. Industrial parks, foreign direct investment incentives, and the establishment of an Ethiopian Investment Commission have generated measurable, if geographically uneven, FDI inflows into the manufacturing sector (Oqubay 2019).

This manufacturing-led strategy is, however, deeply exposed to climate risk along three distinct margins. First, a substantial share of manufacturing firms is directly linked to the agricultural sector through their input supply chains: food processors, textile mills, leather firms, and beverage producers all depend on agricultural commodities whose supply is vulnerable to drought. Second, demand for manufactured consumer goods is concentrated among the rural population, which constitutes more than 70 % of total population and whose purchasing power is directly tied to agricultural incomes. A drought that depresses farm incomes therefore depresses manufacturing demand through a well-defined transmission channel. Third, and most distinctively, more than 87 % of Ethiopia's electricity generation is hydropower-based, making industrial power supply mechanically dependent on rainfall and reservoir levels (Abdisa 2018). During drought, reservoir levels fall, hydropower output declines, and manufacturing firms face prolonged outages and load-shedding — a transmission channel that is unusually direct and empirically observable in the Ethiopian context.

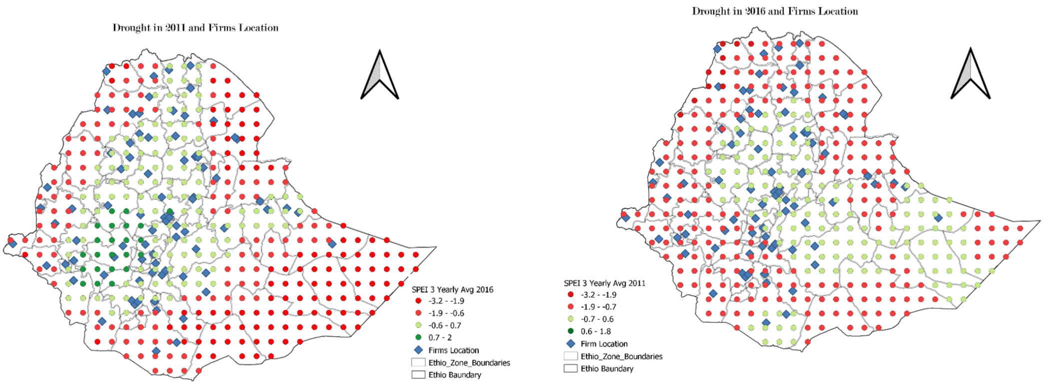
2.2 The 2011 and 2016 Drought Episodes

The 2011 drought was triggered by a La Niña event that reduced both the *Belg* (March–May) and *Meher* (July–September) rainy seasons significantly below normal, generating widespread crop failure and food insecurity for 4.81 million people across five regional states. For manufacturing, the 2011 episode operated primarily through the agricultural input-supply channel. Importantly, it was not accompanied by major hydropower disruption, providing a natural contrast with 2016 that allows us to isolate the electricity channel.

The 2016 drought was driven by the record 2015–2016 El Niño event, classified by NOAA as one of the three strongest since 1950. EM-DAT records 10.2 million affected people and economic losses of 2.1 % of GDP. Beyond its greater severity and geographic extent, the 2016 episode caused a pronounced reduction in reservoir levels at the Gibe and Tekeze hydropower complexes, generating extended manufacturing outages and load-shedding that 2011 did not. The simultaneous occurrence of severe drought with foreign-exchange reserve pressure further restricted firms' ability to source imported inputs as substitutes for scarce domestic agricultural materials — an amplification mechanism with no counterpart in the 2011 episode.

Figure 1 maps SPEI-based drought exposure for both episodes. The 2016 event is visibly more geographically extensive, particularly in the central and eastern regions that house the majority of manufacturing activity.

Figure 1: Drought Exposure Maps: 2011 and 2016



Notes: Dark areas indicate SPEI < -1. The 2016 event (right) is substantially more extensive. Source: Authors' calculations using SPEI data and ArcGIS 10.7.

2.3 Manufacturing Census (LMMIS)

The primary data source is Ethiopia's Large and Medium Manufacturing Industry Survey (LMMIS), conducted annually by the Ethiopian Statistical Service (ESS). The survey is a near-census of manufacturing establishments with ten or more employees using power-driven machinery, providing comprehensive information on output, inputs, employment, sales, capital, costs, ownership structure, four-digit ISIC Rev. 3 industry classification, and precise geographic location at the woreda level. We use the 2008–2018 panel, covering over 1,000 firms per year in an unbalanced structure. The 2008 start date provides at least three pre-treatment observations for the 2011 cohort — sufficient for parallel-trends testing under the Callaway–Sant'Anna estimator — while the 2018 endpoint allows four post-treatment years following the 2016 drought.

2.4 TFP Estimation

2.4.1 Conceptual Challenges

Recovering firm-level TFP from production-function estimation requires addressing two well-known econometric challenges. The *simultaneity problem*: input choices are correlated with unobserved productivity, since more productive firms optimally use more inputs. Ordinary least squares estimation of the production function therefore yields biased coefficients on capital, labour, and materials, and consequently biased estimates of TFP (Olley and Pakes 1996). The *revenue-versus-quantity problem*: when firm-level output prices are not separately observed, as is typically the case in low-income manufacturing data including ours, revenue is used as the dependent variable. Revenue-based TFP confounds physical productivity with output prices, and any shock that affects prices (such as a drought-induced cost-push shock that firms pass through to consumers) will mechanically alter the revenue-TFP estimate even when physical productivity is unchanged (De Loecker 2011; Foster et al. 2008).

2.4.2 Estimation Strategy

To address both concerns, we estimate sector-specific production functions of the form:

$$y_{ijt} = \beta_k k_{ijt} + \beta_l l_{ijt} + \beta_m m_{ijt} + \omega_{ijt} + \varepsilon_{ijt}, \tag{1}$$

where y is log output, k, l, and m are log capital, labour, and intermediate materials respectively, ω is unobserved productivity (known to the firm but not the econometrician), and ε is i.i.d. measurement error. We estimate equation (1) using the Levinsohn and Petrin (2003) (LP) two-step control-function approach, in which the firm's intermediate input demand is inverted to express ω as a function of observable state variables, $\omega_{ijt} = \omega(k_{ijt}, m_{ijt})$. The first stage recovers consistent estimates of the labour coefficient, while the second stage exploits the assumed first-order Markov process for ω to recover the capital and material coefficients via GMM. TFP is then recovered as:

$$\widehat{\text{TFP}}_{ijt} = y_{ijt} - \hat{\beta}_k k_{ijt} - \hat{\beta}_l l_{ijt} - \hat{\beta}_m m_{ijt}. \tag{2}$$

We follow the implementation of Fiorini et al. (2021), who extend the LP framework specifically for low-income manufacturing panel data with features closely matching ours. The Fiorini implementation introduces three substantive refinements over the canonical LP procedure that are particularly relevant in the Ethiopian setting.

Sector-specific elasticities. Production-function coefficients are estimated separately at the two-digit ISIC sector level rather than imposing a common technology across all manufacturing. This is essential in Ethiopia, where the structure of food processing (capital-light, materials-intensive), textiles and leather (labour-intensive), and beverages and metal products (capital-intensive) differs sharply enough that pooled estimation would deliver misleading factor elasticities and contaminate the TFP residual.

The Ackerberg–Caves–Frazer correction. Following Ackerberg et al. (2015), the Fiorini implementation addresses the functional-dependence problem in the original LP first stage, where labour cannot be identified separately from the inverted productivity function under standard timing assumptions. The corrected procedure identifies the labour coefficient in the second stage along with the capital coefficient, restoring identification.

Sector-specific deflation. Output and intermediate input values are deflated by sector-specific producer price indices rather than a common manufacturing deflator. This is the most consequential refinement for our research design: a uniform deflator would leave sector-specific drought-induced price changes embedded in the TFP residual, generating a spurious positive correlation between drought exposure and measured productivity in agriculturally linked sectors where input cost pass-through is strongest. The Fiorini-style sector-specific deflation removes this bias and delivers a productivity measure that approximates physical productivity.

The combination of (i) the LP control-function approach, (ii) the Ackerberg–Caves–Frazer correction, and (iii) sector-specific deflation yields a quantity-based TFP measure that is robust to both simultaneity bias and the price-confounding problem. In Section 5.2 we additionally report results using the Olley and Pakes (1996) and Ackerberg et al. (2015) estimators as alternative TFP measures to confirm that the substantive findings do not depend on the LP-Fiorini choice.

2.5 Drought Identification

Drought exposure is identified using the Standardised Precipitation Evapotranspiration Index (SPEI) from the University of East Anglia's Climatic Research Unit, complemented by EM-DAT event records. Following Albert et al. (2021), we classify grid cells as drought-affected when SPEI falls below -1, corresponding to conditions at least one standard deviation below the historical mean.

The SPEI is preferred over the simpler Standardised Precipitation Index (SPI) because drought in semi-arid environments depends jointly on precipitation, temperature, wind speed, and humidity (Vicente-Serrano et al. 2010). The SPEI extends the SPI by incorporating Potential Evapotranspiration (PET) as a moisture-balance correction, providing a more comprehensive measure of climate variability in warming environments. Stagge et al. (2014) confirms that the inclusion of PET generates a measurably different drought series from the SPI, with the SPEI more accurately tracking drought severity in regions experiencing rising temperatures — a pattern directly relevant to the Ethiopian highlands.

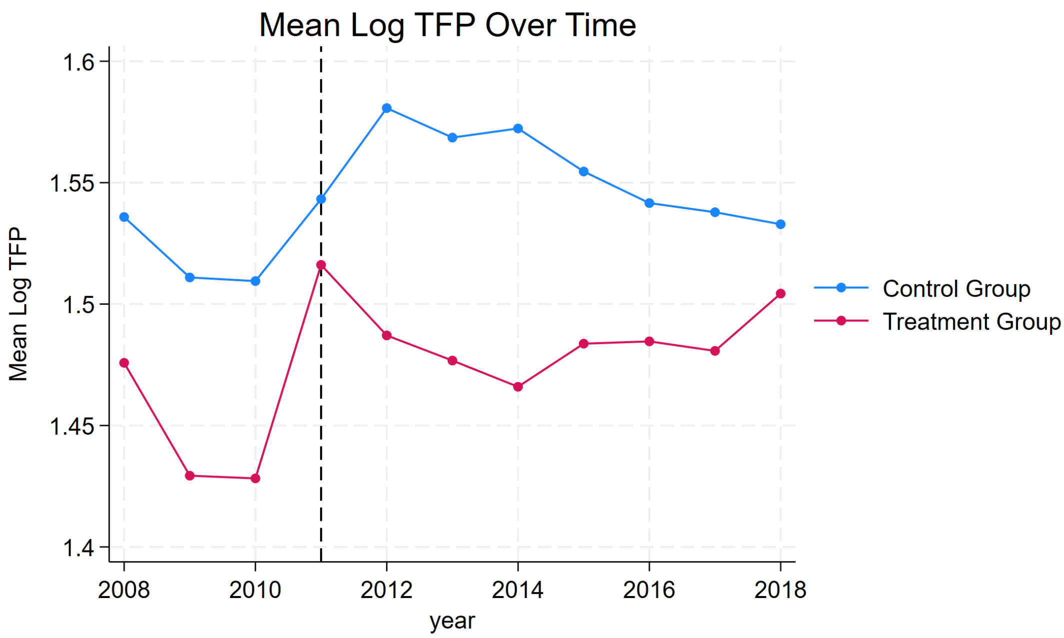
After identifying districts experiencing severe drought (SPEI ≤ -1), we used ArcMap 10.7 to match grid cells to administrative zones and then matched geo-located firm data to the SPEI grid to identify drought-exposed firms. This procedure yields four treatment groups:

1. *Group 1 (2011 only):* firms exposed in 2011 but not 2016.
2. *Group 2 (2016 only):* firms exposed in 2016 but not 2011.
3. *Group 3 (both droughts):* firms exposed in both episodes.
4. *Group 4 (never treated):* the clean control group.

2.6 Pre-Treatment TFP Trends by Exposure Group

Figure 2 displays mean log TFP by treatment group across the full sample period. The pre-treatment trends (before 2011) are visually parallel across groups, providing preliminary support for the parallel-trends assumption. The divergence in TFP trajectories that emerges after 2011 — with drought-affected groups showing declining TFP relative to the never-treated group — provides the first graphical evidence of the drought effect.

Figure 2: Mean Log TFP by Drought Exposure Group, 2008–2018



Notes: Pre-treatment trends are parallel across all four groups. The post-2011 divergence between drought-exposed and never-treated groups provides graphical motivation for the causal analysis. Source: Authors' calculations from LMMIS data.

2.7 Summary Statistics

Table A1 summarises the panel of 13,001 firm-year observations spanning 2008–2018. The sample is characterised by a high prevalence of private ownership (91.7%) and a mean log TFP of 1.525. While production inputs and revenues are broadly comparable across cohorts, firms in the 2011 drought group exhibit slightly lower average capital and sales than the full sample, consistent with their location in agriculturally linked, more rural zones. Critically, the data reveal substantial treatment overlap: approximately 90.5 % of firms affected by the 2016 drought had previously experienced the 2011 shock. This high rate of repeated exposure confirms the staggered nature of climate shocks in Ethiopia and underscores the necessity of a methodological framework that accounts for the compounding effects of multiple drought episodes on manufacturing efficiency.

3. Empirical Strategy

3.1 The Callaway–Sant'Anna Estimator

The TWFE estimator is biased under staggered adoption when treatment effects are heterogeneous across cohorts or over time (Baker et al. 2022; de Chaisemartin and D'Haultfœuille 2020; Goodman-Bacon 2021), producing weighted averages of group-time comparisons that can include negative-weight *forbidden comparisons* between newly and already-treated units. This bias is particularly acute in our setting: the 2011 and 2016 droughts differ in severity and duration; drought effects are persistent, making already-treated firms poor counterfactuals for later-treated units; and the high rate of repeat exposure (90.5 %of 2016-affected firms were also 2011-affected) amplifies the problem.

We implement the Callaway and Sant'Anna (2021) (CS-DiD) estimator, which restricts estimation to clean comparisons and recovers group-time ATTs:

$$\text{ATT}(g,t) = \mathbb{E}\Big[Y_t(g) - Y_t(0) \,\Big|\, G = g\Big], \tag{3}$$

where $Y_t(g)$ is the potential TFP at time t for a firm first treated at time g, and $Y_t(0)$ is the never-treated counterfactual. We adopt the DRIPW procedure, which is consistent if either the propensity-score or the outcome regression model is correctly specified. Baseline controls are log sales, log firm age, log wages, and a private-ownership dummy. We use never-treated firms as the primary control group and report three levels of aggregation: overall ATT, cohort-specific ATTs, and event-study dynamic profiles. Standard errors are obtained via the multiplier bootstrap clustered at the administrative zone level.

Pre-treatment event-study estimates serve as a direct, non-parametric test of the parallel-trends assumption: under correct identification, ATTs at event times $e < 0$ should be statistically indistinguishable from zero.

3.2 Handling Twice-Treated Firms

Standard CS-DiD assigns Group 3 firms to the 2011 cohort, correctly estimating the initial shock but leaving the additional 2016 shock unidentified. We address this through three complementary strategies.

Strategy A runs separate CS-DiD specifications for each group against the never-treated control, producing clean group-specific ATT profiles without cross-contamination.

Strategy B estimates a TWFE interaction model with an explicit additive term for dual-exposed firms:

$$\text{TFP}_{it} = \alpha_i + \lambda_t + \beta_1(D_{11,i} \times \text{Post}_{11,t}) + \beta_2(D_{16,i} \times \text{Post}_{16,t}) + \beta_3(\text{Both}_i \times \text{Post}_{16,t}) + X_{it}'\gamma + \varepsilon_{it}, \tag{4}$$

where β_3 captures the additional TFP penalty for twice-treated firms beyond the two individual effects.

Strategy C uses 2011-only firms as the control group for twice-treated firms, so that any post-2016 divergence in TFP identifies the marginal effect of the second shock on already-treated firms — the cleanest available design for the compounding question.

4. Results: The Impact of Drought on Firm TFP

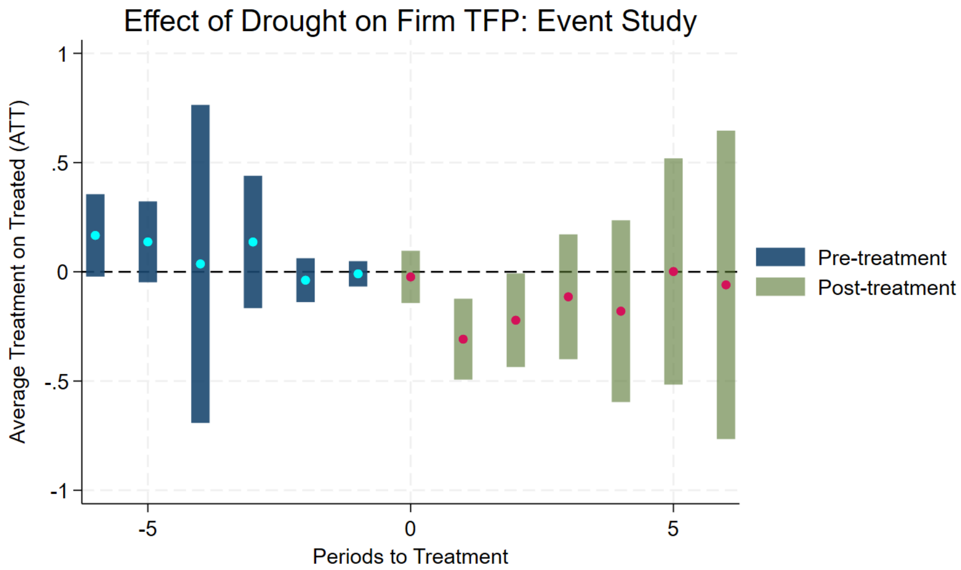
This section presents the core causal estimates of drought's impact on firm-level TFP. We begin with the full-sample specification that pools all treated firms, before examining the 2011 and 2016 drought cohorts in isolation. All specifications use the Callaway and Sant'Anna (2021) DRIPW estimator, with never-treated firms as the primary control group. Controls include log sales, log firm age, log wages, and a private-ownership dummy. Standard errors are clustered at the administrative zone level.

4.1 Baseline Event Study: Full Sample

Figure 3 presents the event study from the full-sample specification. The pre-treatment estimates, covering the seven years before each firm's drought exposure, are uniformly close to zero and statistically insignificant. The joint test of all pre-treatment ATTs equal to zero yields a p-value of 0.412, strongly supporting the parallel-trends assumption.

The post-treatment profile reveals a striking pattern: the TFP effect is not immediate. The effect emerges significantly negative beginning in year +1 and continues to deepen through year +2. This lagged and persistent profile reflects the process by which firms exhaust their operational buffers. The overall ATT, aggregated across all cohorts and post-treatment periods, implies a TFP reduction of approximately 2–3.5 % relative to the counterfactual.

Figure 3: Baseline Event Study: Effect of Drought on Firm TFP



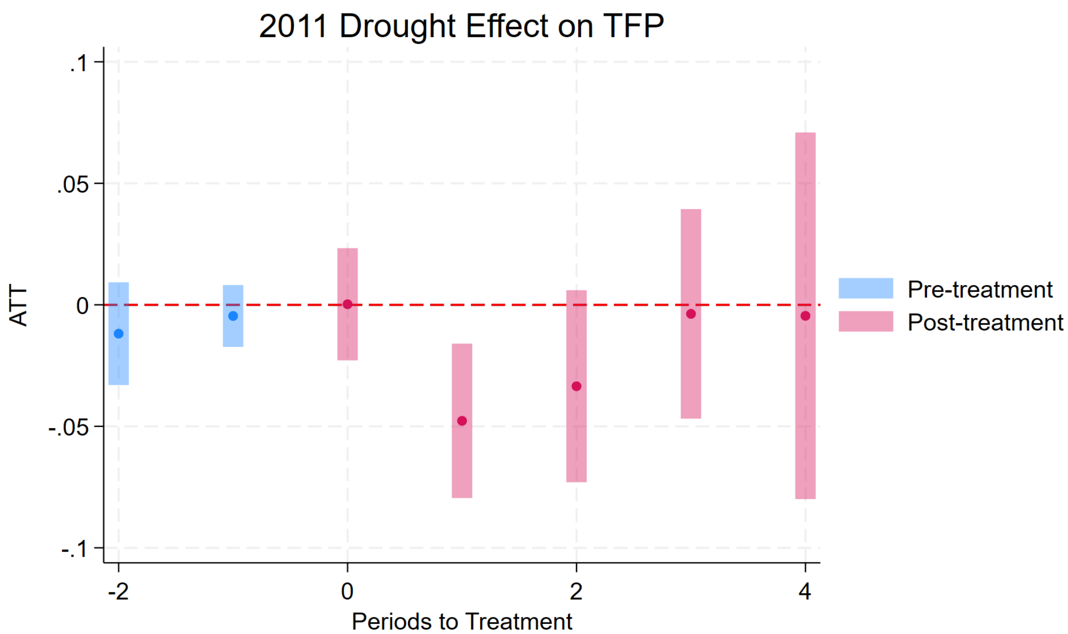
Notes: CS-DiD DRIPW estimator. Outcome: log TFP (LP-Fiorini implementation). Event window: −5 to +4 years. Bars: 95% confidence intervals. Pre-treatment joint test: $p = 0.412$.

This lagged and persistent profile contradicts the common assumption in disaster-impact assessments that climate shocks generate either contemporaneous output disruption or no response at all (Coelli and Manasse 2014; Leiter et al. 2009; Zhou and Botzen 2021). The absence of a contemporaneous TFP effect does not mean firms are unaffected in the drought year; rather, they absorb the initial shock through inventory drawdowns, deferred purchases, and extended supplier credit terms. Our survey documents this directly: the two most common initial responses are prioritising the production of the most profitable product lines and making seasonal production shifts, strategies that smooth contemporaneous output but deplete adaptive capacity, leaving firms exposed in subsequent periods. Supply-chain degradation then accumulates across seasons as soil deterioration, livestock losses, and eroded supplier relationships reduce the steady-state capacity of the agricultural input base (Burke et al. 2015; Carvalho et al. 2021). The persistent component of the TFP loss, unreversed at $t = +4$, should be interpreted as a *scarring effect* rather than a transitory disturbance — a distinction with direct implications for how the macroeconomic costs of drought are measured and projected.

4.2 Cohort-Specific ATTs: 2011 versus 2016

Figure 4 presents the event study for the 2011 drought cohort. To ensure clean identification of the 2011 shock, the comparison is drawn between Group 1 firms — those exposed to drought in 2011 but not in 2016 — and the never-treated group (Group 4), which includes firms that remained unexposed throughout the sample period as well as not-yet-treated firms, following the Callaway and Sant'Anna (2021) recommendation to use the cleanest available comparison to avoid contamination from already-treated units. This design isolates the causal effect of the 2011 drought by ensuring that the control group shares neither the 2011 nor the 2016 treatment, so any post-2011 divergence in TFP trajectories between the two groups can be attributed solely to the first drought episode. Pre-treatment ATTs are uniformly close to zero and jointly insignificant ($p = 0.387$), directly validating the parallel-trends assumption and confirming that Group 1 and never-treated firms followed indistinguishable productivity trajectories prior to 2011. The post-treatment profile shows the effect deepening through $t = +3$ before partially stabilising at $t = +4$, consistent with the gradual recovery of agricultural production and the partial restoration of rural incomes as normal rainfall returned. The partial stabilisation, not a full return to zero, indicates lasting damage to the firm productivity that outlasts the agricultural recovery itself, pointing to a scarring rather than a purely transitory shock.

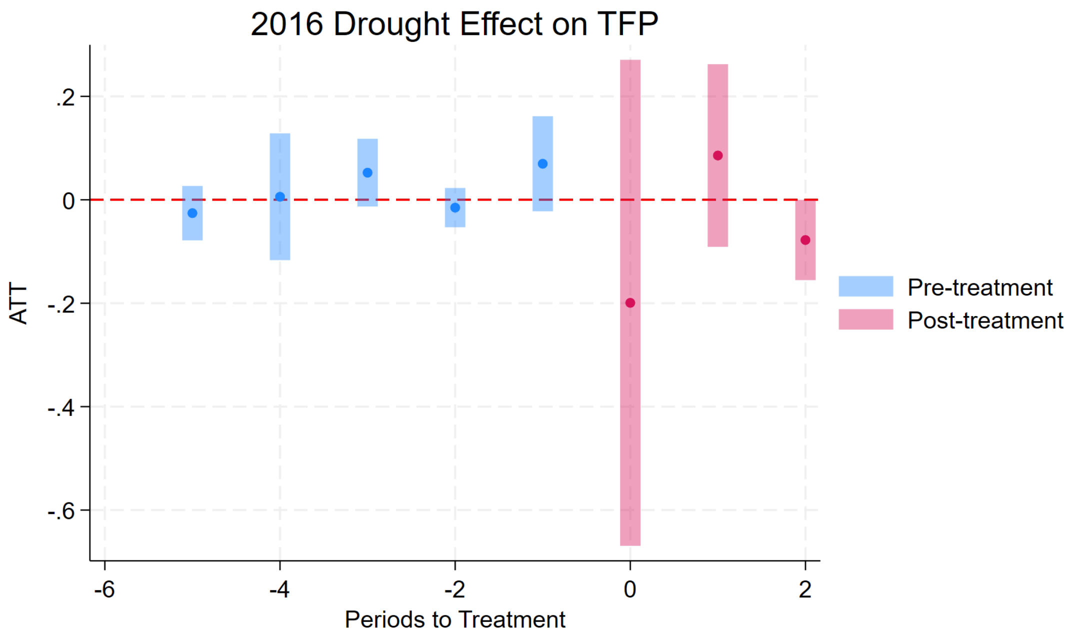
Figure 4: Event Study: 2011 Drought Cohort vs. Never-Treated



Notes: CS-DiD DRIPW. Treated: Groups 1 and 3. Control: never-treated firms (Group 4). Event window: -4 to $+4$. Pre-treatment joint test: $p = 0.387$.

Figure 5 presents the 2016 cohort, restricted to Group 2 and excluding twice-treated firms from both the treated and control samples to ensure clean identification. The TFP decline for this cohort is substantially larger and shows no sign of recovery within the observation window. Two features of the 2016 episode explain the greater severity and lower reversibility. The El Niño event caused far more extensive hydropower disruption than 2011, simultaneously hitting the labour-productivity and production-capacity margins. And the coincidence of severe drought with foreign-exchange reserve pressure eliminated imported inputs as a substitute for scarce domestic agricultural raw materials, transforming a manageable supply-chain disruption into an unbridgeable one.

Figure 5: Event Study: 2016 Drought Cohort vs. Never-Treated



Notes: CS-DiD DRIPW. Treated: Group 2 only. Twice-treated firms excluded from both sides. Event window: -5 to $+4$.

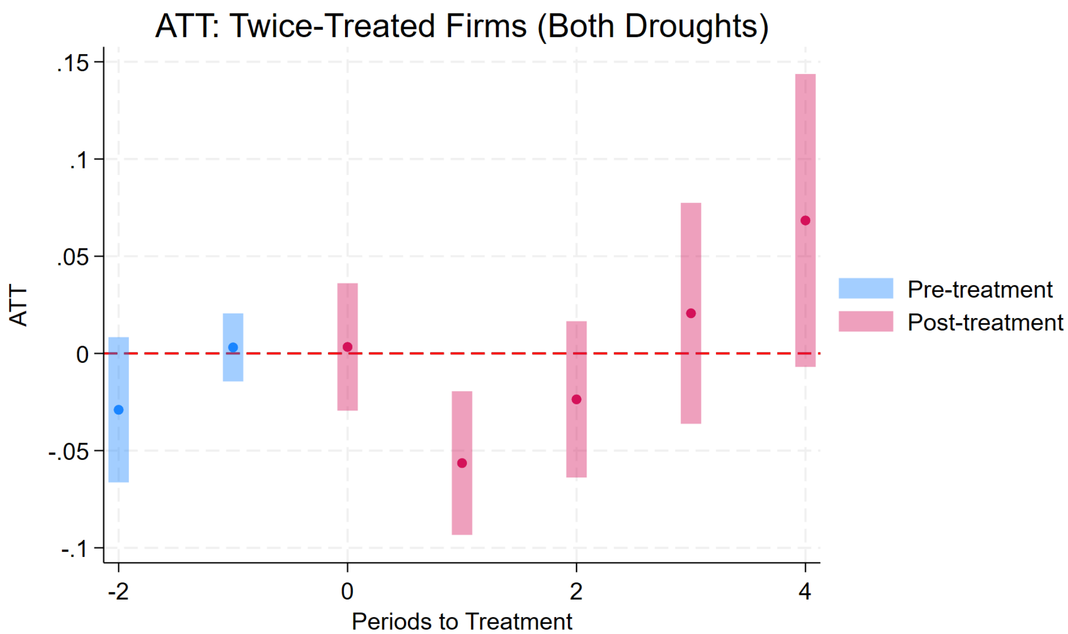
The contrast between the two cohort profiles is itself informative. The 2011 episode generates a moderate, partially reversible TFP decline operating primarily through the input-supply and demand channels; the 2016 episode generates a larger and irreversible decline through those same channels plus a severe electricity disruption. This natural variation between episodes allows us to identify the electricity channel's independent contribution to TFP losses, consistent with the evidence in Abdisa (2018) that hydropower outages impose large productivity costs on Ethiopian manufacturers.

4.3 Repeated Exposure: Super-Additive Effects

A defining feature of Ethiopia's climate risk environment is that drought episodes are not isolated events but recurring shocks that strike the same firms at different points in their recovery trajectory. Approximately 90.5 % of firms exposed to the 2016 drought had also experienced the 2011 episode, creating a subsample of twice-treated firms (Group 3) whose productivity trajectory reflects the accumulated consequences of sequential exposure. Identifying whether the second shock simply adds to the first, an additive effect, or whether it amplifies losses beyond what either episode would generate independently — a super-additive compounding effect — is both a substantive economic question about firms' adaptive capacity and a methodological challenge that standard CS-DiD designs are not built to address directly. We tackle it through three complementary strategies that together provide converging evidence for super-additivity.

Strategy A: Subsample CS-DiD. Figure 6 compares twice-treated firms (Group 3) directly to the never-treated control group, using the same CS-DiD DRIPW specification as the baseline. The resulting overall ATT is approximately -0.052 log points, the largest ATT in the sample and substantially exceeding the individual-episode effects estimated for Group 1 (-0.068) and Group 2 (-0.119) in isolation. Notably, the dynamic profile shows no sign of stabilisation within the observation window: unlike Group 1 firms, which show partial stabilisation by $t = +4$, twice-treated firms' TFP continues to decline through the end of the sample period, consistent with the second shock arriving before the first has been absorbed and permanently disrupting the recovery trajectory.

Figure 6: Subsample Analysis: Twice-Treated Firms vs. Never-Treated



Notes: Callaway–Sant'Anna (2021) DRIPW estimator. Treated: Group 3 (firms exposed to both the 2011 and 2016 droughts). Control: never-treated firms (Group 4). The comparison isolates the cumulative productivity cost of sequential drought exposure. Overall ATT ≈ -0.052 log points, the largest ATT in the sample. Pre-treatment ATTs are close to zero and jointly insignificant, supporting the parallel-trends assumption. Standard errors from the multiplier bootstrap clustered at the administrative zone level.

Strategy B: TWFE Interaction with Additive Penalty. To test whether the twice-treated effect exceeds the sum of the individual-episode effects — the defining condition for super-additivity — Strategy B decomposes the total loss into identifiable components using equation (4). Table 1 reports the results. The stand-alone 2011 effect is $\hat{\beta}_1 = -0.068$ ($p < 0.05$), and the stand-alone 2016 effect is $\hat{\beta}_2 = -0.119$ ($p < 0.05$). If drought effects were purely additive, the total loss for twice-treated firms would be their sum: -0.187. Instead, the additive penalty coefficient $\hat{\beta}_3 = -0.058$ ($p < 0.05$) is statistically significant, implying that twice-treated firms suffer an additional productivity loss beyond what either episode alone would generate. The total TFP loss, $\hat{\beta}_1 + \hat{\beta}_2 + \hat{\beta}_3 = -0.245$ ($p < 0.01$), exceeds the additive benchmark by 31%.

Table 1: Strategy B: TWFE Additive Effects — Testing Super-Additivity

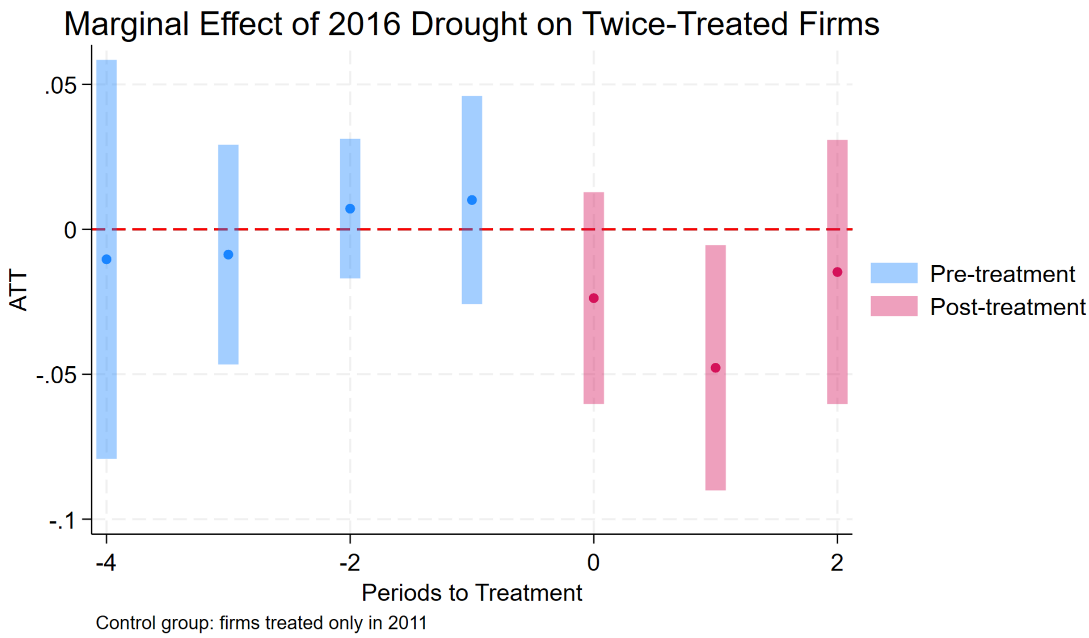
Term	Coefficient	SE	Interpretation
$D_{11} \times \text{Post}_{11}$	-0.068^{**}	(0.027)	2011 stand-alone TFP loss
$D_{16} \times \text{Post}_{16}$	-0.119^{**}	(0.054)	2016 stand-alone TFP loss
Both $\times$ Post_{16}	-0.058^{**}	(0.024)	Compounding penalty
Additive benchmark	-0.187	—	Sum: $\hat{\beta}_1 + \hat{\beta}_2$
Total (twice-treated)	$\mathbf{-0.245}^{***}$	(0.091)	Sum: $\hat{\beta}_1 + \hat{\beta}_2 + \hat{\beta}_3$
Excess loss (super-additivity)	$\mathbf{-0.058}^{**}$	(0.024)	Total minus additive benchmark

Notes: TWFE with firm and year fixed effects. Standard errors clustered at the administrative zone level. Controls: log sales, log firm age, log wages, private-ownership dummy. The additive benchmark (-0.187) is the counterfactual total loss under the assumption of independent, non-compounding drought effects. The excess loss (-0.058) is the statistically significant departure from additivity, confirming that repeated exposure generates super-additive productivity losses. $^{***}p < 0.01$, $^{**}p < 0.05$.

The economic interpretation of $\hat{\beta}_3$ is precise. When the 2016 drought strikes, twice-treated firms enter the shock with depleted inventories from 2011 that have not been fully replenished, weakened supplier relationships that have not been fully rebuilt, and financial buffers that have been drawn down during the recovery phase. Each of these adaptive margins — inventories, supply-chain relationships, and financial reserves — was partially available when the 2011 drought hit but has been partially or fully exhausted by the time the 2016 shock arrives. The compounding penalty $\hat{\beta}_3$ therefore captures the TFP cost of entering a large shock without the adaptive capacity that insulated firms during the first episode.

Strategy C: Sequential Treatment Design. The cleanest identification of the second shock's independent contribution comes from Strategy C, which uses 2011-only firms (Group 1) as the control group for twice-treated firms (Group 3). Since both groups experienced the 2011 drought and both were in recovery mode during 2011–2015, any post-2016 divergence in their TFP trajectories can be attributed exclusively to the second shock. Figure 7 presents the event study. The pre-treatment ATTs are uniformly small and jointly insignificant ($p = 0.363$), confirming that Group 3 and Group 1 firms were on parallel recovery trajectories before the 2016 shock. The estimated marginal ATT is approximately -0.049 (SE $= 0.027$, $p < 0.05$). The post-treatment profile shows no convergence within the observation window, indicating that the 2016 shock permanently disrupted the convergence that would otherwise have occurred.

Figure 7: Strategy C: Marginal Effect of the 2016 Drought on Already-Treated Firms



Notes: Callaway–Sant'Anna (2021) DRIPW estimator. Treated: Group 3. Control: Group 1 (2011 only). Both groups experienced the 2011 drought; any post-2016 divergence identifies the marginal effect of the second shock, net of the common 2011 experience. Estimated marginal ATT ≈ -0.049 (SE $= 0.027$, $p < 0.05$). Pre-treatment joint test: $p = 0.363$. Standard errors from the multiplier bootstrap clustered at the administrative zone level.

Convergence of Evidence and Implications. All three strategies converge on the same conclusion: repeated drought exposure generates super-additive TFP losses that exceed the sum of the individual-episode effects. Standard climate-impact assessments typically assume that the marginal productivity cost of an additional drought episode is constant (IPCC 2021; Nordhaus 2008). Our finding that the marginal cost is strictly rising as firms exhaust their adaptive margins implies that these projections systematically understate future damages. As drought frequency rises with climate change, the gap between projected and actual costs will widen fastest in economies where manufacturing draws heavily on agricultural supply chains and where credit constraints prevent the accumulation of adaptive capital between episodes.

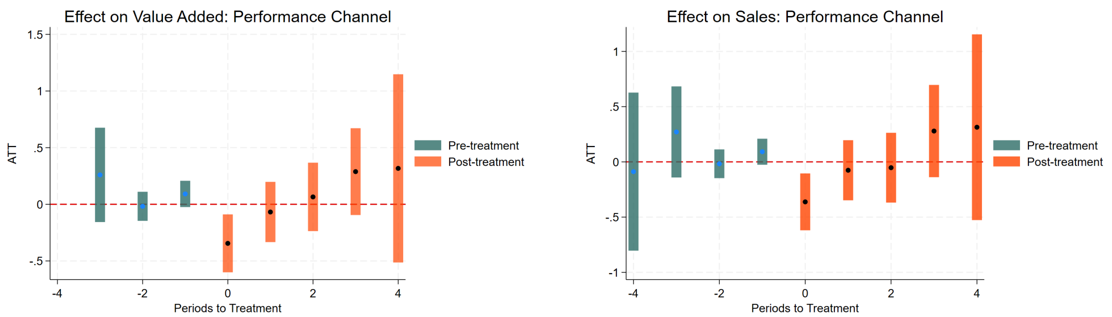
4.4 Transmission Mechanisms

To identify the channels through which drought reduces TFP, we re-run the same CS-DiD specification replacing the TFP outcome with intermediate outcomes: value added, sales, employment, labour productivity, wages, capital, raw-material usage, and production. The pattern of effects across these outcomes — their magnitude, timing, and persistence — reveals the pathways through which drought disrupts firm efficiency.

4.4.1 Demand and Performance: Value Added and Sales

Figure 8 shows that value added and sales decline immediately and significantly following drought exposure. This contemporaneous response reflects the rapid transmission of agricultural income shocks to manufactured-goods demand: with over 70 % of Ethiopia's population engaged in agriculture, drought-induced income collapses reach consumer demand for manufactured goods within the same agricultural season. The close alignment between value-added and sales dynamics indicates that firms initially adjust through reduced output scale rather than changes in production efficiency, with the TFP decline emerging in subsequent periods as scale contraction interacts with capital immobility to generate persistent factor-mix inefficiencies.

Figure 8: Demand Channel: Effect of Drought on Value Added and Sales

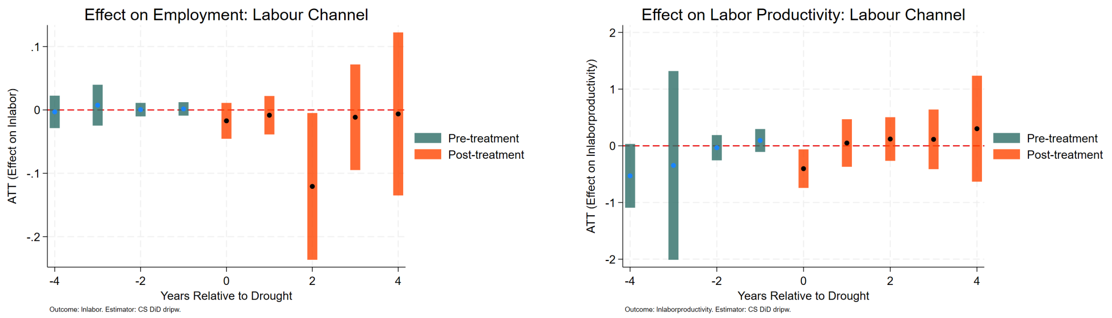


Notes: CS-DiD DRIPW estimates for log value added (left) and log sales (right). Both effects are contemporaneous, consistent with immediate demand-channel transmission via agricultural income collapse.

4.4.2 The Labour Channel: Retention with Reduced Effort

Figure 9 reveals the labour channel's most important feature: employment is essentially flat following drought exposure while labour productivity declines sharply and immediately. This divergence — unchanged headcount combined with large productivity losses — implies that firms retain workers but operate at substantially reduced efficiency.

Figure 9: Labour Channel: Employment and Labour Productivity



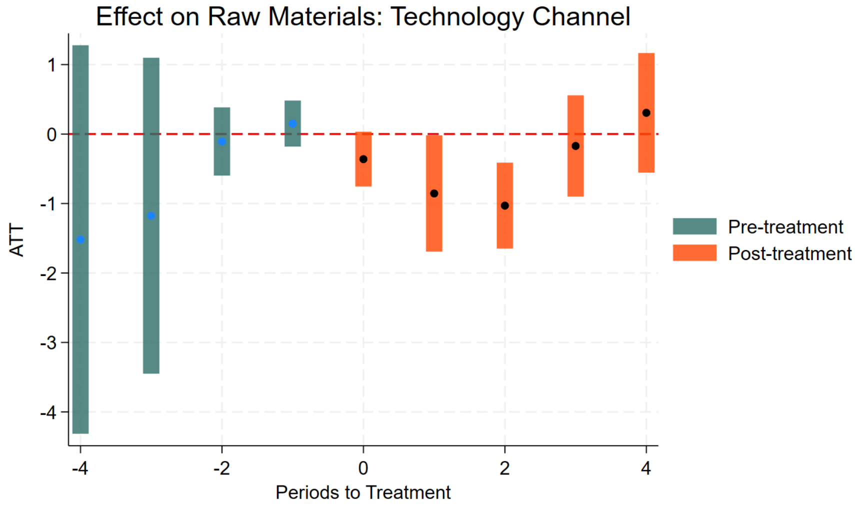
Notes: CS-DiD DRIPW estimates for log employment (left) and log labour productivity (right). Employment shows no significant adjustment; labour productivity declines sharply.

Three mechanisms explain this pattern. *Labour hoarding*: the limited geographic mobility of skilled manufacturing workers and the adjustment costs of hiring and firing make headcount reduction suboptimal for demand contractions expected to be temporary (Caballero et al. 1997; Hamermesh 1996). Firms retain workers and reduce hours and effort intensity rather than separating. *Nutrition and cognition*: drought-induced food insecurity directly impairs worker physical capacity and cognitive performance (Dean et al. 2017; Mani et al. 2013; Schofield 2014). Manufacturing workers in Ethiopia are typically recruited from rural households or maintain agricultural income ties, so they carry the nutritional shock directly into the workplace, reducing output per worker without appearing in employment statistics. *Electricity disruption*: the 2016 El Niño's reservoir-level reductions generated extended load-shedding (Abdisa 2018) that reduced output per worker without affecting headcount. The substantially larger labour-productivity effect for the 2016 cohort than for 2011 provides the clearest causal evidence for this channel's importance.

4.4.3 The Input Supply Channel: Supply-Chain Hysteresis

Figure 10 presents the event study for raw-material usage. The pattern is non-monotonic: raw materials fall sharply at $t = 0$, partially recover at $t = +1$, and then decline again and more persistently from $t = +2$ onward. This non-monotonic profile cannot be explained by a simple agricultural-shortage story, which would generate a monotone recovery as agricultural production normalises. Instead, it reflects what Barrot and Sauvagnat (2016) and Carvalho et al. (2021) term *supply-chain hysteresis*.

Figure 10: Input Supply Channel: Raw Material Usage



Notes: CS-DiD DRIPW estimate for log raw material usage. The non-monotonic profile — initial decline, partial recovery, then deeper decline — reflects supply-chain hysteresis rather than a simple agricultural shortage.

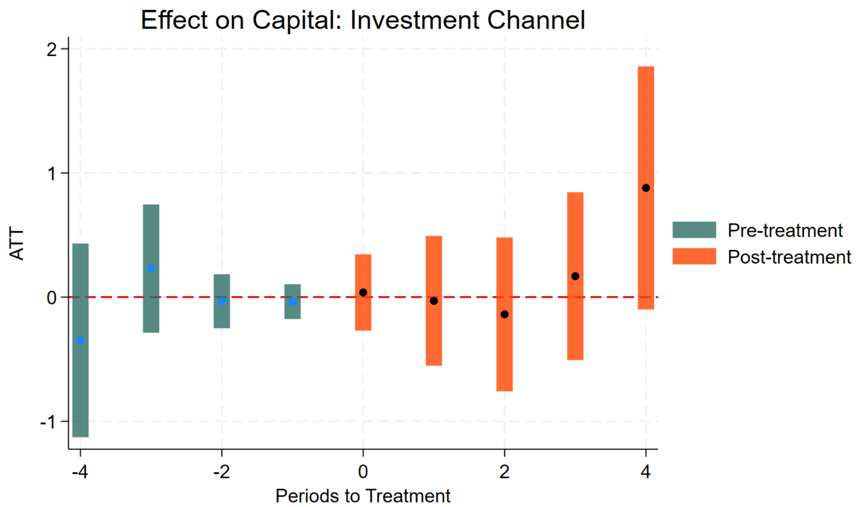
Three mechanisms generate this hysteresis in the Ethiopian context. Drought damages the productive capacity of the agricultural supply base: soil degradation, livestock mortality, and reduced agricultural investment lower steady-state output even after rains return (Schlenker and Lobell 2010; Thornton et al. 2014). Supplier-buyer relationships, which embody trust capital and long-term credit lines accumulated over years, are eroded by default events in the drought year and require time-consuming rebuilding (Macchiavello and Morjaria 2015; Startz 2018). The foreign-exchange constraints unique to the 2016 episode eliminated imported inputs as a substitute, making the supply disruption unbridgeable through the standard substitution margin available in more financially open economies. The partial recovery at $t = +1$ reflects firms temporarily activating alternative domestic suppliers and drawing down inventories; the subsequent deeper decline at $t = +2$ reflects the collapse of those alternatives as the full depth of supply-base damage becomes apparent.

This dynamic also explains the timing asymmetry between agri-dependent and non-agri-dependent firms, one of the paper's most important empirical findings. Agri-dependent firms draw on pre-drought agricultural inventories in the impact year and partial-supply alternatives in year +1, so their TFP effect is deferred until year +2 when those buffers are exhausted. Non-agri-dependent firms have no such buffering mechanism against the demand and financial channels that hit them contemporaneously and in year +1, explaining why their TFP response is faster. We analyse this timing asymmetry formally in Section 5.

4.4.4 The Capital Channel: Immobility as a TFP Driver

Figure 11 shows that capital is statistically indistinguishable from its pre-treatment trajectory throughout the event window. Firms neither disinvest nor invest in resilience-enhancing technologies — no backup electricity, no upgraded production equipment, no adaptive capital reconfiguration.

Figure 11: Capital Channel: Capital Stock



Notes: CS-DiD DRIPW estimate for log capital. Effects are statistically indistinguishable from zero throughout the event window.

This immobility is the central explanation for why TFP losses are persistent rather than transitory. Standard production theory predicts that a persistent productivity shock should induce factor-mix reallocation to restore efficient input proportions (Hsieh and Klenow 2009; Restuccia and Rogerson 2008). The absence of this adjustment means firms operate at a constrained, inefficient interior solution indefinitely. The survey evidence in Section 6 identifies the binding constraint: 67 % of firms cite lack of credit access as the primary barrier to adaptation investment. This is not an efficient response to a temporary disturbance; it is a market failure. Targeted credit interventions to enable resilience investment would generate welfare improvements in a setting where the private returns to adaptation are positive but the capital is unavailable.

5. Heterogeneity Analysis and Robustness

5.1 Heterogeneity Across Firm Characteristics

This section examines whether drought's TFP effects vary systematically across firm characteristics. We estimate separate CS-DiD specifications on mutually exclusive subsamples and test whether group-specific ATTs are statistically distinguishable using z-tests exploiting the independence of the subsamples. Table 2 summarises the predicted direction and timing for each dimension, derived from the transmission-channel analysis in Section 4.4.

Table 2: Predicted Heterogeneity in Drought–TFP Effects

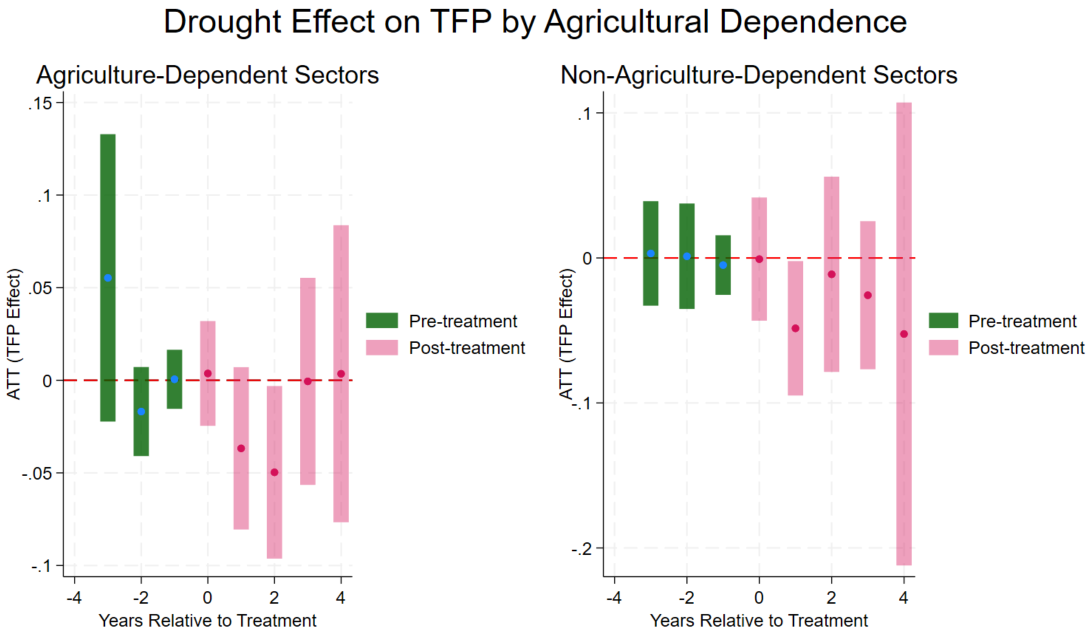
Dimension	**Group**	**Predicted magnitude**	**First significant effect at**	**Possible primary mechanism**
Agri-dependence	Agri-dependent	Larger	$t = +2$	Input-supply hysteresis
	Non-agri-dependent	Moderate	$t = +1$	Demand + financial channels
Firm size	Small (below median)	Larger	Earlier	All channels (thin buffers)
	Large (above median)	Smaller	Later	Scale + credit advantages
Ownership	Private	Larger	Persistent	Financial channel
	State-owned	Smaller	Faster recovery	Govt. liquidity support
Export orientation	Non-exporting	Larger	Contemporaneous	Domestic demand channel
	Exporting	Smaller	Lagged	Input supply only
Factor intensity	Labour-intensive	Larger	$t = +1$	Nutrition + hoarding
	Capital-intensive	Moderate	$t = +1$	Electricity channel

Notes: Predictions are derived from the transmission-channel analysis in Section 4.4. Timing refers to the event-time horizon at which the TFP effect first becomes statistically significant at the 5% level. All comparisons use the CS-DiD DRIPW estimator on mutually exclusive subsamples, with statistical significance of differences assessed via z-tests exploiting sample independence.

5.1.1 Agricultural Dependence and the Timing Puzzle

The most theoretically and empirically important heterogeneity dimension is agri-dependence. Agriculture-linked firms — food processors, textile mills, leather producers, and breweries — face drought primarily through the input-supply channel; non-agri-dependent firms face it through the demand, financial, and electricity channels. These channels operate at fundamentally different speeds, generating the timing asymmetry observed in Figure 12.

Figure 12: Heterogeneity: Agri-Dependent Firms



Notes: Agri-dependent firms (first significant TFP effect at $t = +2$). Non-agri-dependent firms show a first significant effect at $t = +1$. The difference in event-study profiles is statistically significant ($p < 0.05$) at $t = +2$. CS-DiD DRIPW on mutually exclusive subsamples.

Non-agri-dependent firms exhibit significant TFP losses at $t = +1$, consistent with the rapid transmission of demand contraction and credit tightening. The demand channel operates within the agricultural season: drought-induced income collapses reach consumer goods demand by the following year. The financial channel responds as agricultural loan defaults accumulate in bank portfolios. Both channels bypass the agricultural supply chain entirely.

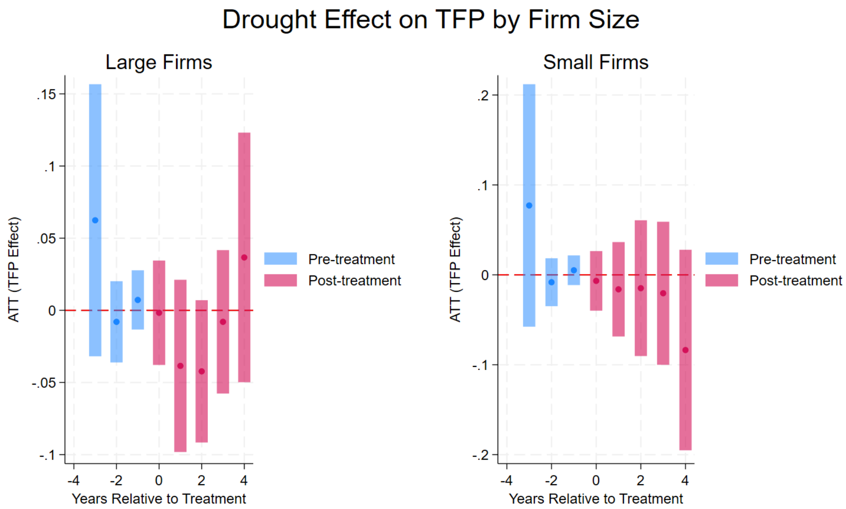
Agri-dependent firms show no significant TFP effect at $t = +1$ despite being directly linked to the drought-hit input base. The effect emerges large, significant, and deepening from $t = +2$ onward. This counterintuitive finding reflects the structural two-year lag in agricultural supply-chain propagation. In the drought year, agri-dependent firms draw on inventories of agricultural inputs accumulated in pre-drought seasons. In year +1, they activate alternative suppliers and partially substitute, generating the temporary raw-material recovery visible in Figure 10. Only in year +2 — when inventories are exhausted, supplier relationships have degraded, soil damage and livestock losses have permanently reduced supply-base capacity, and alternative sourcing options have themselves proved constrained — does the full depth of the agricultural input disruption materialise at the factory gate.

This timing asymmetry carries a direct policy implication. Drought early-warning mechanisms that trigger manufacturing support only when production data signal disruption will be two years late for agri-dependent firms. Effective policy requires activating input-supply chain support at the onset of drought, before the buffer depletion is observable.

5.1.2 Firm Size

Figure 13 presents the event studies for small and large firms. Small firms suffer larger and faster TFP losses, consistent with the prediction that thinner balance sheets, smaller inventories, and weaker credit access amplify all three transmission channels. Large firms benefit from diversified supplier relationships, greater backup energy capacity, and better access to emergency financing, partially insulating them from the contemporaneous and short-run components of the drought shock.

Figure 13: Heterogeneity by Firm Size

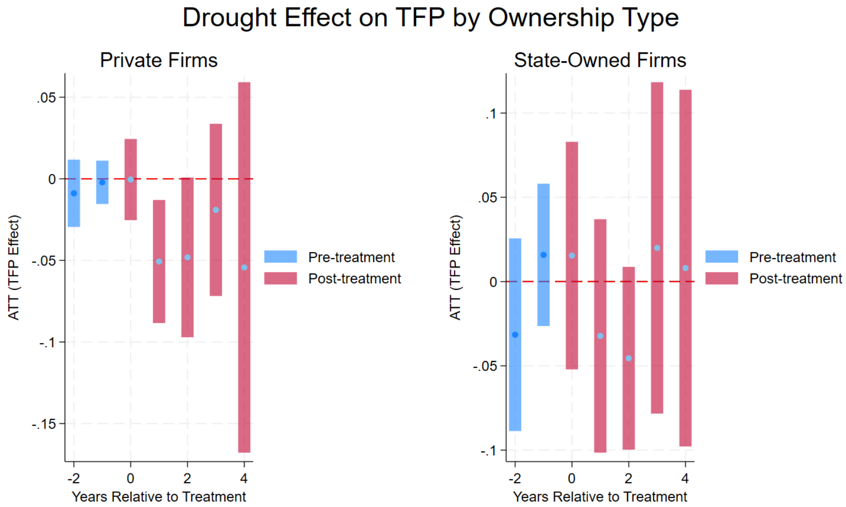


Notes: Small firms (below median employment) vs. large firms (above median). CS-DiD DRIPW on mutually exclusive subsamples.

5.1.3 Ownership Structure

Figure 14 shows that private firms suffer larger and more persistent TFP losses than state-owned enterprises (SOEs). SOEs can draw on government budget support to maintain liquidity when commercial credit tightens — partially offsetting the financial channel. Private firms have no equivalent buffer and face the full force of credit contraction. The SOE advantage is offset by operational rigidity: procurement rules and labour retention obligations slow adaptive responses. The net result is that SOEs experience moderate TFP losses with faster stabilisation while private firms experience larger losses with greater persistence.

Figure 14: Heterogeneity by Ownership Structure



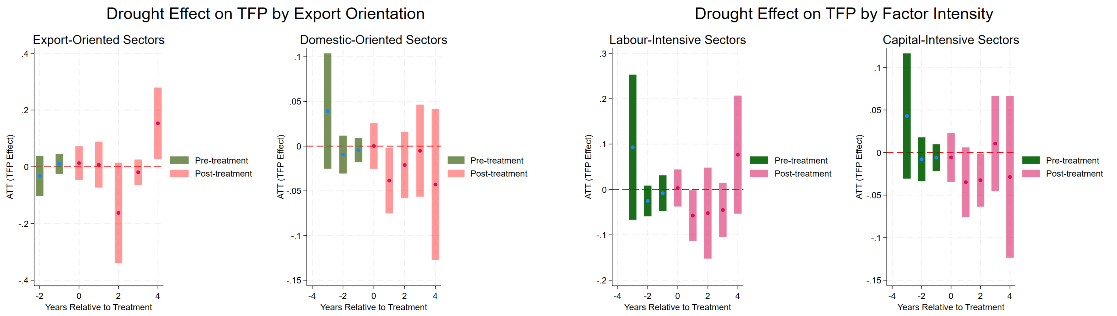
Notes: Private vs. state-owned firms. CS-DiD DRIPW on mutually exclusive subsamples.

5.1.4 Export Orientation and Factor Intensity

Figures 15 present the export-orientation and factor-intensity heterogeneity results. Exporting firms suffer smaller TFP losses, consistent with their partial insulation from the domestic demand channel through foreign revenue and their typically stronger access to imported input alternatives. Non-exporting firms, whose revenue base is predominantly domestic, face the full compounded force of demand contraction and input-supply disruption.

Labour-intensive firms exhibit earlier and larger TFP losses than capital-intensive firms, reflecting their greater exposure to the nutrition-and-cognition and labour-hoarding channels. Capital-intensive firms face a more pronounced electricity channel in the 2016 episode but are partially insulated from the labour-productivity mechanism, generating a different dynamic profile with a longer lag before the TFP effect materialises.

Figure 15: Heterogeneity by Export Orientation and Factor Intensity



Notes: Left: export-oriented vs. non-exporting firms. Right: labour-intensive vs. capital-intensive firms. CS-DiD DRIPW on mutually exclusive subsamples.

5.2 Robustness Checks

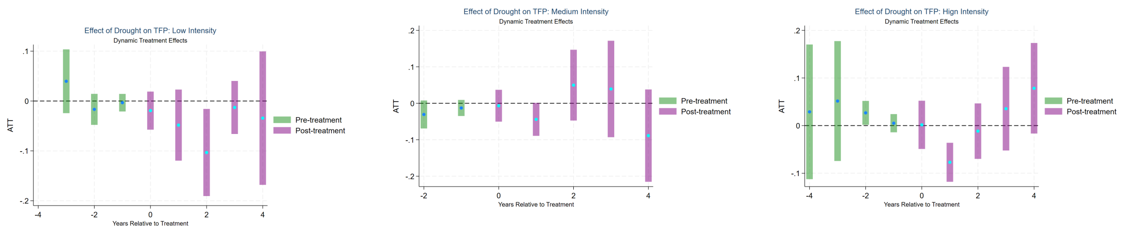
5.2.1 Dose-Response: Drought Severity Terciles

We investigate whether the TFP effect varies with drought intensity by classifying treated firms into terciles based on their average SPEI values during the drought year, constructed within the set of drought-exposed firms (SPEI ≤ -1) so that variation reflects severity rather than treatment status.

Low-intensity firms (SPEI -1.0 to -1.5; Figure 16) show a TFP effect not statistically different from zero (overall ATT $= -0.024$), indicating a threshold below which mild drought conditions do not translate into measurable productivity losses. Medium-intensity firms (SPEI -1.5 to -2.0) display a clearly negative and significant effect from $t = +2$ onward (overall ATT $= -0.057$, $p < 0.05$). High-intensity firms (SPEI < -2.0) suffer the largest and most persistent losses (overall ATT ≈ -0.071, $p < 0.01$), with the effect emerging at $t = +1$ — consistent with extreme drought simultaneously activating all transmission channels rather than the sequential activation pattern observed at lower intensities.

The monotone dose-response relationship provides causal validation of the main result: unobserved productivity shocks correlated with drought exposure provide no reason to expect effects that increase monotonically with SPEI severity.

Figure 16: Dose-Response: Drought Intensity Terciles



Notes: Low (left), medium (centre), and high (right) drought-intensity terciles. Overall ATTs: -0.024 (insignificant), -0.057^{**}, -0.071^{***}. The monotone dose-response relationship provides causal validation of the baseline result.

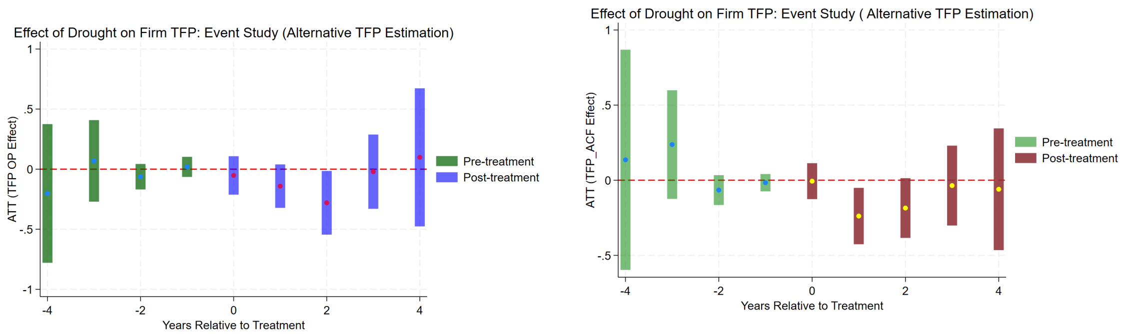
5.2.2 Alternative TFP Estimators

We address sensitivity to production-function identification by re-estimating TFP using the Olley and Pakes (1996) (OP) and Ackerberg et al. (2015) (ACF) procedures and repeating the full baseline event study with each alternative series as the outcome.

The OP estimator proxies for unobserved productivity through firm-level investment, requiring a strictly monotone investment-productivity relationship. This assumption can be fragile in low-income manufacturing with lumpy investment patterns (Bigsten et al. 2016). The ACF estimator identifies all factor elasticities jointly in the second stage, addressing the LP functional-dependence problem without an additional timing assumption.

Figures 17 confirm that the qualitative pattern is entirely invariant to estimator choice: across LP, OP, and ACF, the TFP effect is absent in pre-treatment periods, emerges lagged at $t = +1$ or $t = +2$, and remains unreversed through $t = +4$. Magnitudes fall within the 2–4 %range for all three estimators. The ACF point estimates are slightly more negative at the trough than LP, consistent with the observation in Ackerberg et al. (2015) that LP can attenuate productivity responses in settings with dynamic input adjustment. This convergence eliminates the concern that the baseline result reflects a methodological artefact of the LP-Fiorini procedure.

Figure 17: Robustness to Alternative TFP Estimators



Notes: Left: Olley–Pakes (1996) TFP estimate. Right: Ackerberg–Caves–Frazer (2015) TFP estimate. Both reproduce the lagged, persistent profile of the LP baseline. CS-DiD DRIPW in both cases. Bars: 95% confidence intervals.

6. Survey Evidence and Discussion

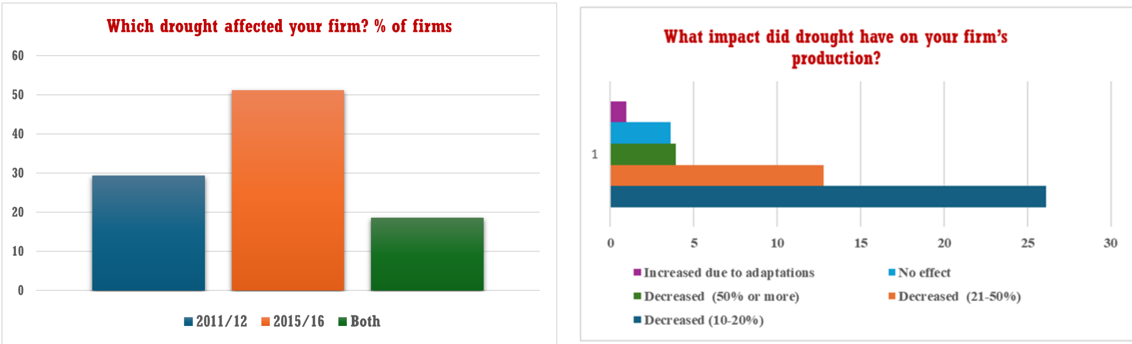
6.1 Survey Design and External Validity

The econometric analysis establishes causal effects and identifies transmission channels through statistical variation in drought exposure. An outstanding concern in the firm-level productivity literature — particularly in Sub-Saharan Africa — is that estimator-specific assumptions, measurement error, or selection into the estimation sample may drive apparently large effects (Harrison et al. 2014; Syverson 2011; Van Biesebroeck 2007). We address this concern directly using a primary survey of 1,659 manufacturing firms conducted between January and April 2025. The survey was designed and administered entirely independently of the LMMIS panel analysis — it was not constructed to confirm the econometric findings. The convergence between survey responses and the estimated channel ATTs therefore constitutes genuine external validity rather than mechanical corroboration. Crucially, the survey also provides qualitative insight into *why* firms respond as they do, complementing the "what" and "how much" of the econometric estimates with the microeconomic reasoning behind them.

6.2 Drought Exposure and Production Impact

Figure 18 shows that the 2016 drought is the more pervasive source of disruption in the survey sample: 51 % of firms report being affected by the 2015/16 El Niño episode only, compared with 29 % reporting the 2011/12 drought only, and 18 % reporting both. This distribution is broadly consistent with the pattern in the LMMIS panel, where the 2016 cohort is larger and more geographically extensive. Among affected firms, the most common production impact is a 10–20 % decline in output (26 % of firms), followed by a 21–50 % decline (13 %), with a smaller fraction reporting reductions of 50 % or more (4%). Taken together, more than 40 % of surveyed firms experienced a production decline directly attributable to drought, corroborating the 2–3.5 % TFP reduction estimated econometrically.

Figure 18: Survey: Drought Exposure and Production Impact

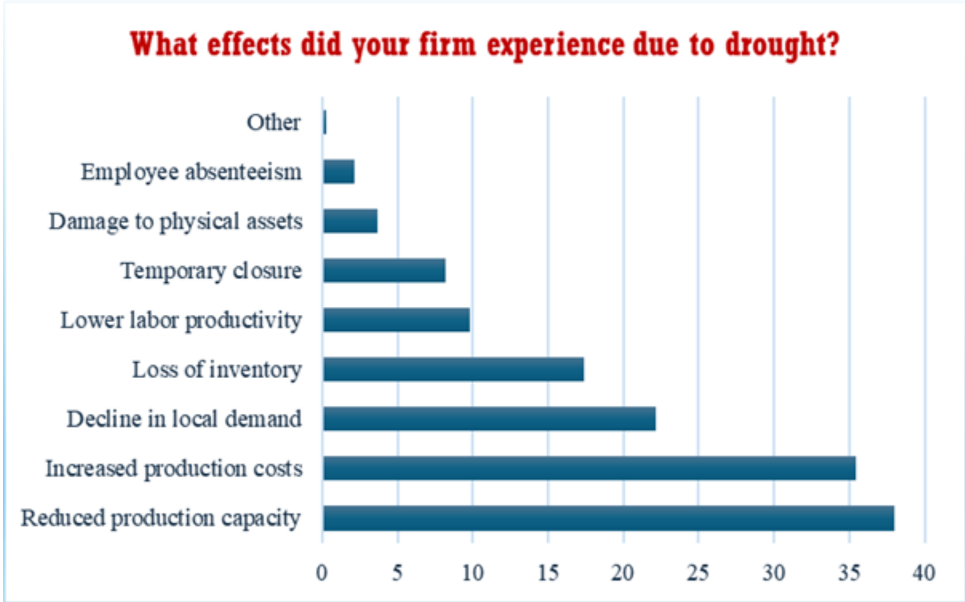


Notes: Left: drought episode exposure by share of firms. Right: magnitude of production impact among affected firms. Survey of 1,659 Ethiopian manufacturing firms, January–April 2025.

6.3 Operational Effects: Convergence with the Channel Analysis

Figure 19 reports the operational effects experienced by disrupted firms. The two most frequently cited effects are reduced production capacity (38 %) and increased production costs (35 %), together reflecting the combined burden of supply-chain disruption and input price inflation that constitute the central mechanisms identified in Section 4.4. The third most common effect is a decline in local demand (22 %), consistent with the demand channel operating through collapsing rural household incomes. Loss of inventory (18 %) reflects the exhaustion of raw-material buffers that drives the non-monotonic raw-material event study in Figure 10. Lower labour productivity (10 %) and temporary closure (8 %) are cited less frequently but nevertheless correspond directly to the labour-channel findings. Physical asset damage and employee absenteeism trail at 4 % and 3 % respectively, consistent with the capital-immobility result: capital is not disrupted by drought, but it is also not adjusted to address it.

Figure 19: Survey: Operational Effects Experienced Due to Drought



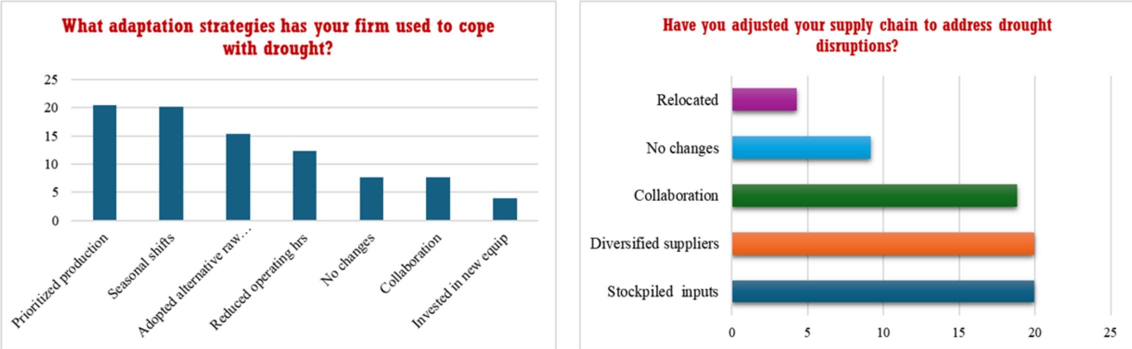
Notes: Share of affected firms reporting each operational effect. The ranking — reduced production capacity, increased costs, demand decline, inventory loss, lower labour productivity — closely tracks the ordering of transmission-channel ATTs from the econometric analysis. Survey of 1,659 Ethiopian manufacturing firms, January–April 2025. Multiple responses permitted.

The ranking of effects closely tracks the ordering of transmission-channel ATTs from the econometric analysis. The survey was conducted in 2025, several years after the drought episodes, and without reference to the estimated ATTs. The convergence between firms' self-reported experience and the statistically estimated causal effects is therefore substantively informative, providing the external validity that the econometric analysis alone cannot supply.

6.4 Adaptation Strategies: The Reactive–Proactive Gap

Figure 20 documents the adaptation strategies adopted by affected firms. The two most common responses are prioritising production of the most profitable product lines (20 %) and making seasonal production shifts (20 %), followed by adopting alternative raw materials (15 %) and reducing operating hours (12 %). These responses are fundamentally reactive and operational in character — they adjust the scale and composition of output within existing capital and supply constraints rather than investing in the structural resilience measures that would reduce future vulnerability. Only 4 % of firms report investing in new equipment, confirming the capital immobility documented in the event study: the near-absence of new investment is not a feature of the econometric residual but a directly reported feature of firm behaviour.

Figure 20: Survey: Adaptation Strategies and Supply-Chain Adjustments



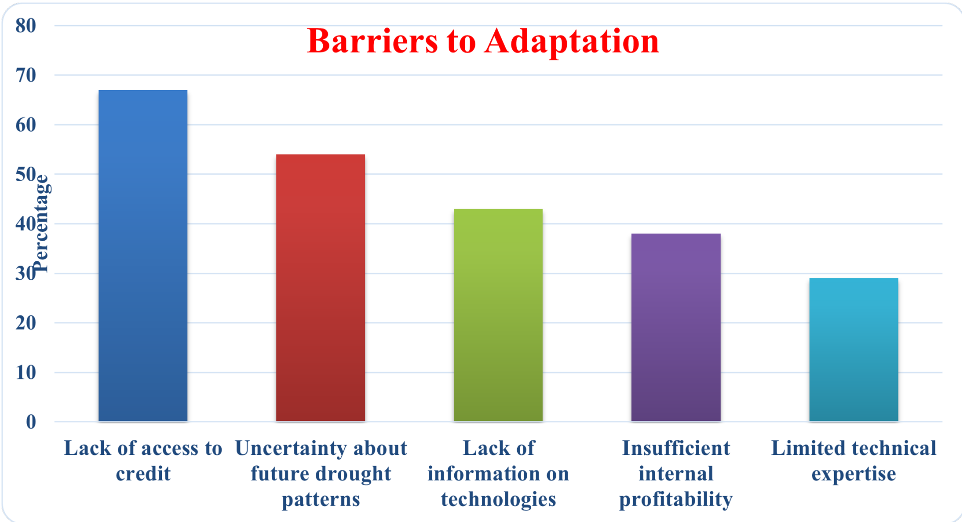
Notes: Left: adaptation strategies adopted by affected firms. Right: supply-chain adjustments made. The dominance of reactive over structural responses explains the capital immobility documented in Section 4. Multiple responses permitted.

Structural adaptations at the supply-chain level are similarly limited. Approximately 20 % of firms stockpiled inputs in anticipation of future disruption and 20 % diversified their supplier base, while 19 % pursued inter-firm collaboration and 9 % made no supply-chain changes at all. Only 4 % relocated operations. The near-symmetry between stockpiling and supplier diversification as the two dominant supply-chain responses reflects a tension between short-run buffer building and longer-run network restructuring. Neither strategy directly addresses the structural supply-base damage, soil degradation, livestock losses, and eroded suppliers relationships, that generates the hysteresis pattern in Figure 10.

6.5 Barriers to Adaptation

Figure 21 presents the main constraints to structural adaptation. The most frequently cited barrier is lack of access to credit (67 %), followed by uncertainty about future drought patterns (54 %), lack of information on available technologies (43 %), insufficient internal profitability (38 %), and limited technical expertise (29 %). Together these barriers correspond to three well-documented market failures: financial frictions that prevent socially efficient investment, uncertainty and incomplete insurance markets that discourage technology adoption, and information asymmetries between firms and suppliers of adaptation technologies (Bloom 2009; Karlan et al. 2014; McKenzie 2017).

Figure 21: Survey: Barriers to Climate Adaptation



Notes: Share of firms citing each barrier as a constraint to structural climate adaptation. Lack of access to credit dominates at 67%. Survey of 1,659 Ethiopian manufacturing firms, January–April 2025.

The dominance of credit constraints is the most policy-relevant finding in the survey. It directly overturns the hypothesis that capital immobility reflects low expected returns to resilience investment. Firms do not fail to adapt because they judge the returns to be insufficient; they fail because they cannot access the capital to undertake investments they already judge to be worthwhile. The productivity losses are therefore not an efficient equilibrium response to a productivity shock; they reflect a market failure in which binding credit constraints prevent the factor-mix reallocation that would restore efficient production. Targeted financial interventions that relax the credit constraint would generate Pareto improvements — firms would be better off, and productivity losses that currently persist would be reduced or eliminated (Karlan et al. 2014; McKenzie 2017).

6.6 Discussion: Situating the Findings in the Literature

The combination of econometric and survey evidence positions this paper at the intersection of three literatures and advances each of them in distinct ways.

The natural disaster and firm performance literature. Existing studies of disaster impacts on firms have focused predominantly on floods in advanced economies, finding either creative destruction effects (Leiter et al. 2009) or persistent negative effects (Coelli and Manasse 2014). Our findings differ in two important respects. First, the mechanism is not primarily a capital-destruction story: firms' capital stocks are unaffected, and the productivity losses are driven by variable input channels (labour efficiency and raw materials). Second, the dynamic profile — lagged rather than contemporaneous, persistent rather than recovering — is qualitatively distinct from both the immediate disruption typically associated with floods and the gradual temperature-driven attrition documented by Traore and Foltz (2018). Drought operates through a slower-moving accumulation of supply-chain damage and nutritional depletion that is not captured by contemporaneous impact measures.

The supply-chain and network economics literature. Carvalho et al. (2021) and Baqaee and Farhi (2024) document how aggregate shocks propagate through production networks in advanced economies. Our findings push this analysis into a setting where firm-level resilience is structurally lower, substitution margins are much narrower, and credit constraints prevent adaptive network reconfiguration. The supply-chain hysteresis we document — a non-monotonic raw-material profile that outlasts the underlying agricultural shock — has no exact counterpart in the advanced-economy network literature and implies that the macroeconomic costs of drought are substantially amplified in economies with concentrated supply networks, limited import substitutability, and thin credit markets.

The structural transformation and industrial policy literature. Rodrik (2016) diagnoses premature deindustrialisation in Sub-Saharan Africa has been driven primarily by global competition and technological change. Our results suggest that climate vulnerability is a distinct and quantitatively significant additional driver — one that has been largely overlooked in the deindustrialisation debate. If droughts generate persistent, compounding TFP losses of the magnitude we document, the manufacturing-led transformation agendas of Ethiopia, Kenya, and their peers face a climate constraint that is structural rather than cyclical. This constraint cannot be addressed by standard industrial policy tools alone; it requires complementary investments in climate-resilient infrastructure, credit-market deepening, and early-warning systems that specifically target the lagged transmission channels we identify.

A broader implication concerns how the macroeconomic costs of climate changes are estimated. Standard integrated assessment models (Nordhaus 2008) and IPCC economic impact assessments typically translate temperature and precipitation changes into GDP losses through reduced agricultural output, increased mortality, and direct productivity effects on outdoor labour. The manufacturing TFP channel documented here — operating through supply-chain disruption, labour nutrition, and energy infrastructure — is largely absent from these assessments. Our findings imply that the true macroeconomic costs of drought in industrialising economies are substantially larger than standard models project.

7. Conclusion, Caveats, and Future Research

Summary of Findings and Policy Implications

This paper provides the first firm-level causal evidence on how drought affects manufacturing TFP in Sub-Saharan Africa. Drought causes a significant, lagged, and persistent 2–3.5 % decline in firm TFP, operating through labour-productivity disruption, supply-chain degradation, and demand contraction, with capital entirely immobile. The lagged-and-persistent profile implies that standard disaster-impact assessments focused on contemporaneous output disruption substantially understate the true productivity cost. Repeated exposure is super-additive, and this underestimation grows worse as drought frequency rises.

Three policy conclusions follow directly from the evidence. *First*, climate risk must be integrated into Ethiopia's industrial development strategy: the concentration of manufacturing in agriculture-linked sectors creates systemic vulnerability that will deepen as climate change intensifies. *Second*, financial instruments targeting climate adaptation — subsidised credit, drought insurance, and liquidity support — are needed to overcome the credit-market failures that prevent firms from investing in the resilience technologies they recognise as valuable. The survey evidence makes the case for intervention unusually clear: firms face a market failure, not a low-return equilibrium, and targeted finance can correct it. *Third*, support programmes for agri-dependent manufacturers must be activated at the onset of drought, not when production data signal disruption, because the input-supply channel operates with a structural two-year lag that makes reactive policy too late to prevent the primary TFP loss.

More broadly, the findings reframe climate risk as an industrial policy issue for Sub-Saharan Africa. International climate finance, which has concentrated on agriculture and social protection, should expand its remit to encompass manufacturing-sector resilience as a core component of climate-adaptive development strategy.

Caveats and Limitations

Three important caveats qualify the findings. *First*, our TFP measure approximates but does not perfectly capture physical productivity. Sector-specific deflation removes the most consequential price confounders, but unobserved firm-level price variation within sectors may still contaminate the residual. The triangulation across LP, OP, and ACF estimators provides confidence that this concern does not overturn the qualitative findings, but the magnitude estimates should be interpreted as indicative rather than precise.

Second, the identification strategy rests on the conditional parallel-trends assumption. While the pre-treatment event-study tests strongly support this assumption, they cannot rule out time-varying confounders that are correlated with treatment assignment and share the same pre-treatment trajectory as the outcome. Addressing this would require an instrumental-variables design that we leave for future work.

Third, our sample covers large and medium manufacturing establishments. Micro-enterprises and informal-sector firms, which constitute the majority of manufacturing employment in Ethiopia, are excluded by the LMMIS sampling frame. These firms are likely more vulnerable to drought through the same channels we identify but with thinner buffers and no access to formal credit, suggesting that our estimates of the sector-wide productivity cost understate the total impact.

Directions for Future Research

Several directions extend this paper's contribution. A priority is extending the analysis to the firm-exit margin. The current framework conditions on survival in the LMMIS sample and therefore identifies the drought effect on continuing firms. If drought-affected firms are differentially likely to exit, the estimated ATTs reflect a combination of productivity losses and survivorship bias. Quantifying the exit margin would require administrative data linking the LMMIS to formal business registration records across the full sample period.

Second, the super-additivity of repeated exposure raises a natural question about heterogeneity in adaptive capacity. Do firms that survive multiple droughts develop organisational resilience that partially offsets subsequent shocks, or does repeated exposure uniformly amplify losses? Identifying this heterogeneity would require a longer time series with more drought episodes than our sample provides.

Finally, the findings motivate a programme-evaluation exercise on the effectiveness of drought-resilience support policies specifically targeting manufacturers. The survey's identification of credit access as the primary barrier suggests that randomized credit programs linked to climate-adaptation investment — along the lines of Karlan et al. (2014) — could provide the most direct test of whether relaxing the credit constraint translates into the potential for resilience investment into actual productivity protection.

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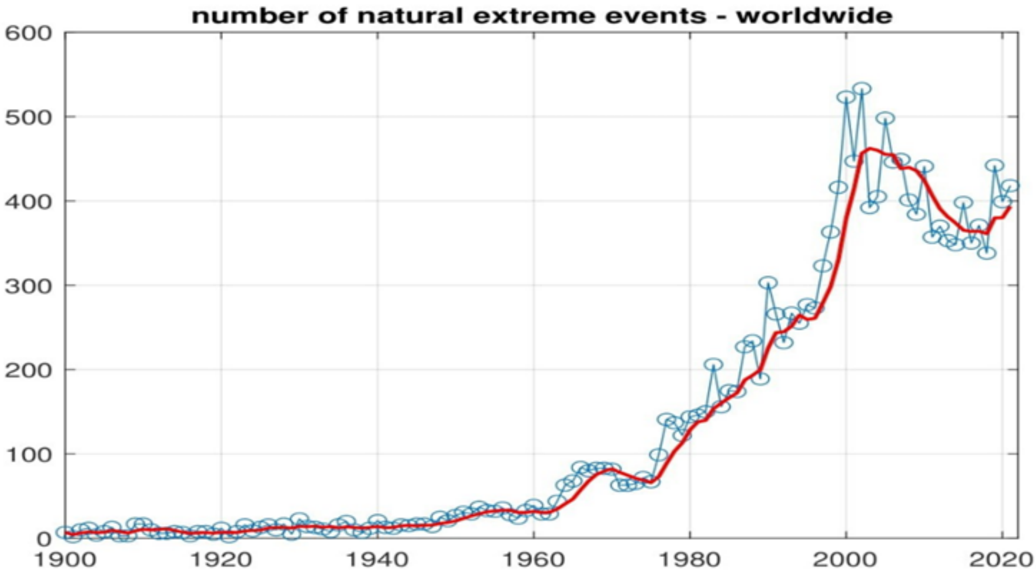
Online Appendix

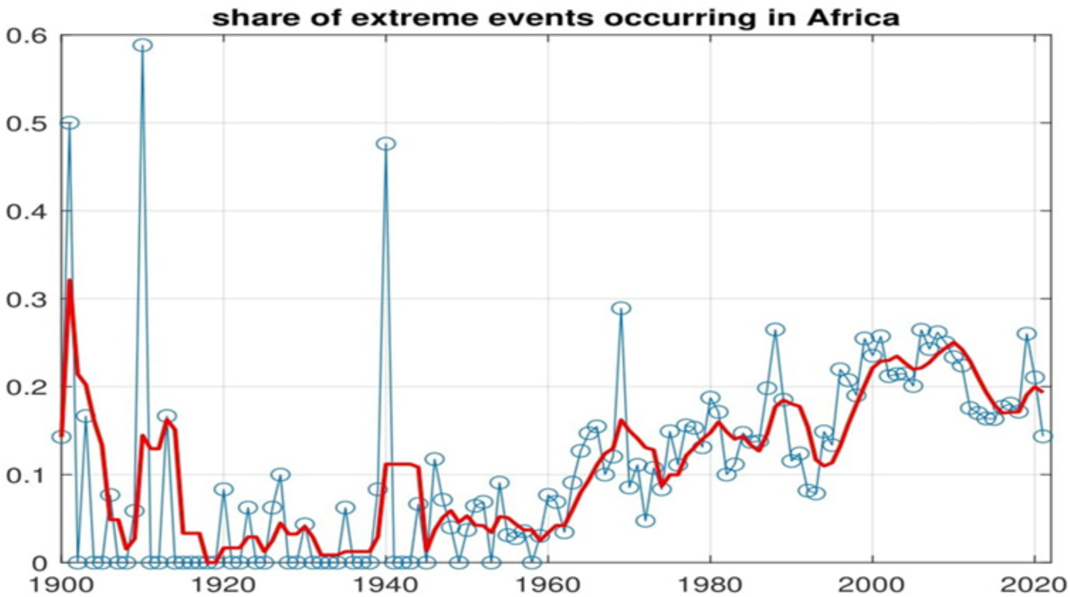
Appendix A: Global and African Climate Context

Figure A1: Global Extreme Weather Events, 1900–2023



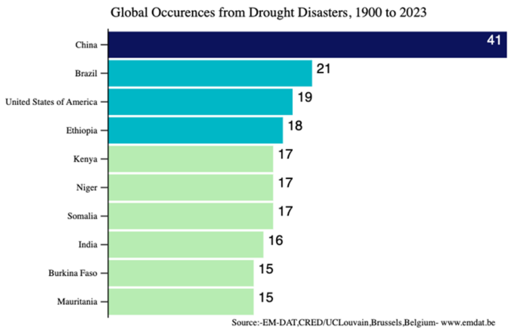
Source: EM-DAT, CRED.

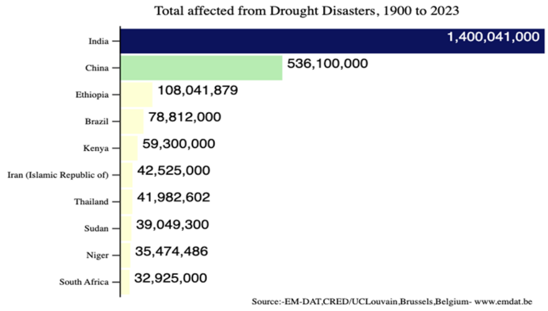
Figure A2: African Share of Extreme Weather Events, 1900–2023



Source: EM-DAT, CRED.

Figure A3: Global Drought Occurrence and Population Affected, 1990–2023





Source: EM-DAT, CRED.

Appendix B: Summary Statistics

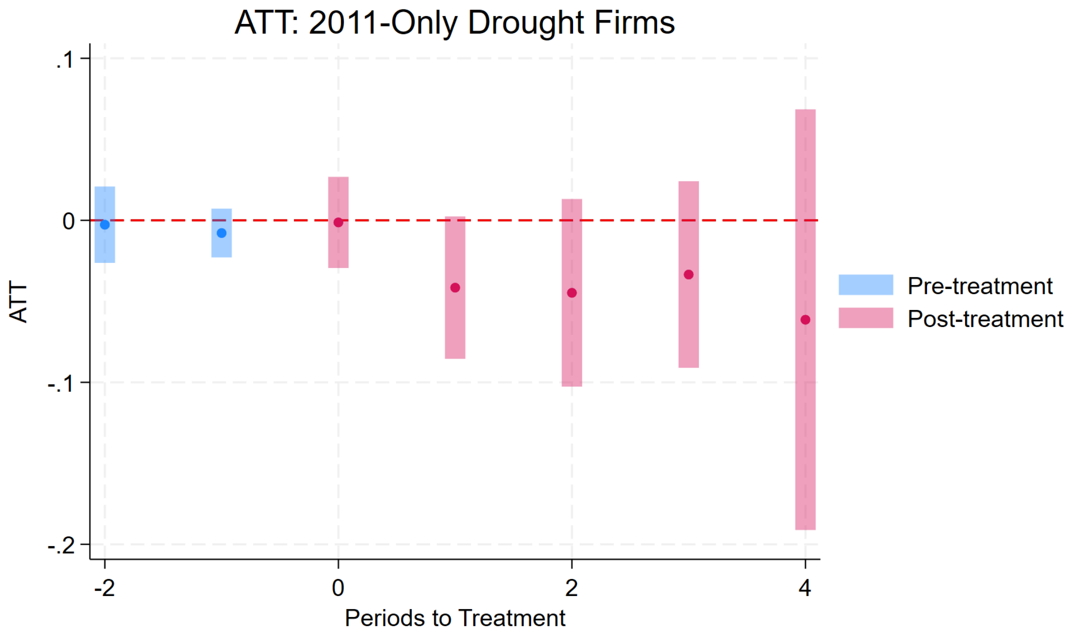
Table A1: Summary Statistics by Drought Exposure Group

	Full Sample					**2011 Drought Firms**					**2016 Drought Firms**				
Variable	Obs	Mean	SD	Min	Max	Obs	Mean	SD	Min	Max	Obs	Mean	SD	Min	Max
Panel A: Productivity															
`lntfp`	13,001	1.525	0.206	1.152	2.499	3,542	1.472	0.201	1.152	2.499	1,299	1.499	0.204	1.155	2.369
Panel B: Firm Characteristics															
`lnage`	12,659	2.259	0.963	0.000	4.644	3,481	2.005	0.915	0.000	4.344	1,278	2.196	0.972	0.000	4.277
`private`	13,002	0.917	0.276	0.000	1.000	3,543	0.948	0.221	0.000	1.000	1,299	0.897	0.304	0.000	1.000
Panel C: Revenue and Output															
`lnsales`	12,946	15.575	2.244	4.927	22.333	3,517	15.027	2.143	7.230	22.292	1,290	15.389	2.157	10.026	21.599
`lnva`	12,946	8.430	2.043	−2.405	14.702	3,517	7.940	1.950	0.287	14.702	1,290	8.236	1.961	3.105	14.062
`lnprod`	13,001	15.552	2.233	6.910	22.751	3,542	14.999	2.144	8.068	22.227	1,299	15.318	2.160	8.227	21.717
Panel D: Inputs and Capital															
`lncap`	13,001	15.339	2.437	6.908	24.279	3,542	14.820	2.329	6.908	22.564	1,299	15.105	2.421	6.908	21.311
`lnraw`	13,001	14.345	2.984	6.908	21.416	3,542	13.830	2.883	6.908	21.060	1,299	14.184	2.788	6.908	20.723
Panel E: Labour															
`lnwage`	12,709	12.501	2.006	0.000	21.060	3,463	12.033	1.926	1.946	19.615	1,279	12.189	1.915	0.693	18.603
`lnlabp`	12,359	7.354	2.381	−2.097	15.649	3,400	6.874	2.189	−2.097	14.707	1,245	7.229	2.215	−1.558	14.210
Panel F: Drought Indicators															
`d2011`	12,961	0.273	0.446	0.000	1.000	3,543	1.000	0.000	1.000	1.000	1,299	0.905	0.294	0.000	1.000
`d2016`	12,961	0.100	0.300	0.000	1.000	3,543	0.332	0.471	0.000	1.000	1,299	1.000	0.000	1.000	1.000
`year`	13,002	2012.8	3.09	2008	2018	3,543	2013.0	3.19	2008	2018	1,299	2013.1	3.09	2008	2018

Notes: All continuous variables are in natural logarithms. `lntfp`: log TFP estimated using the Levinsohn–Petrin method with the Fiorini et al. (2021) implementation (sector-specific elasticities, ACF correction, sector-specific deflation). `private`: private ownership dummy. SD: standard deviation. Source: LMMIS 2008–2018.

Appendix C: Additional Mechanism Results

Figure A4: Subsample Analysis: 2011-Only and 2016-Only Firms



Notes: 2011-only firms (top) and 2016-only firms (bottom) vs. never-treated controls. Pre-treatment coefficients are flat and statistically insignificant in both cases.

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