Global Supply Chain Shocks and the W-Shaped Dynamics of African Industry: The Role of Intra-Regional Trade

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Abstract

This paper examines how global supply chain (GSC) disruptions impact industrialization in African economies. Using a multi-sector framework that accounts for input complementarities and origin-differentiated intermediates, we identify a three-wave shock transmission mechanism. There are: material shortages, lagged agro-industrial links, and delayed capital accumulation, leading to a W-shaped manufacturing response. We test that mechanism with panel SVAR and local projections on African data from 2000 to 2026, and find that GSC disruptions cause an immediate contraction, followed by a deeper secondary downturn and persistent scarring effects. Additionally, using instruments based on the AfCFTA implementation index, we show that countries with stronger regional integration experience weaker responses to global shocks and faster recoveries. The findings suggest a dual role for trade openness: global integration transmits volatility, but regional integration can buffer its effects by allowing substitution across sourcing origins, thereby enhancing industrial resilience in African economies.

Key words: Global Supply Chain Shocks, Industrialization, African Economies, Regional Trade Integration, AfCFTA, Structural VAR, Local projection.
JEL Codes: F14, F15, O14, O55, E32, C32, D58

1 Introduction

Industrialization in small open economies has been highly volatile, reflecting deep exposure to global economic shocks. Episodes such as the collapse of manufacturing activity in the 1980s, the disruptions following exchange rate adjustments in the 1990s, and the recent contraction during the COVID-19 pandemic underscore the sensitivity of industrial output to external conditions. While trade openness is often viewed as a driver of industrialization through market access and technology diffusion (Mignamissi & Nguekeng 2022, Hoekstra 2013), a parallel literature argues that it may instead hinder industrial development by increasing exposure to external shocks and uncertainty (e.g., Araujo et al., 2021, Amoah & Jehu-Appiah, 2022, Özçelik & Özmen, 2023). This tension points to a central but unresolved issue: openness is both a source of growth and a channel of vulnerability in developing economies (Briguglio et al., 2014, Montalbano, 2011). Yet, existing work has largely focused on aggregate volatility, overlooking how global supply chain disruptions propagate across sectors and over time. Understanding the dynamic effects of such shocks on industrialization,

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particularly in the context of increasingly fragmented production systems, remains a first-order question.

Despite a growing body of work on global value chains and production networks, existing theoretical frameworks remain limited in their ability to capture the dynamic and sector-specific mechanisms through which global supply chain disruptions affect industrialization in developing economies. Standard trade models with input linkages, such as those building on Armington-type structures or quantitative trade frameworks (e.g., Caliendo & Parro, 2015), typically focus on static or steady-state responses and emphasize reallocation effects rather than transitional dynamics. Similarly, production network models (e.g., Acemoglu et al., 2012, Oberfield, 2021) highlight the propagation of shocks through input-output linkages but generally abstract from sectoral heterogeneity in adjustment speeds and from the intertemporal structure of production, particularly the role of agriculture and capital accumulation in shaping industrial outcomes. While these frameworks provide important insights into amplification and spillovers, they are not designed to capture non-linear and multi-phase adjustment paths, such as the staggered and potentially non-monotonic responses observed in developing economies. As a result, they offer limited guidance for understanding how global supply chain disruptions translate into industrial dynamics over time, especially in contexts characterized by strong complementarities, delayed transmission channels, and structural dependence on imported inputs.

Identifying the causal and dynamic effects of global supply chain (GSC) disruptions on industrialization poses substantial empirical challenges. First, GSC shocks are inherently global and endogenous to macroeconomic conditions, making it difficult to disentangle exogenous supply disturbances from demand-driven fluctuations. Second, the transmission of such shocks is multi-dimensional and unfolds over time through sectoral linkages, requiring a framework capable of capturing both contemporaneous and lagged interactions across variables. Third, standard reduced-form approaches, such as single-equation regressions or panel fixed effects models, are ill-suited to address these issues, as they impose restrictive dynamics and fail to account for feedback effects and general equilibrium interactions. These limitations are well documented in the macroeconometric literature, which emphasizes the importance of structural identification in dynamic systems (e.g., Christiano et al., 1999, Stock & Watson, 2001, Kilian & Lütkepohl, 2011). In this context, Vector Autoregression (VAR) models and their structural variants provide a natural and powerful framework, as they allow for the joint modeling of multiple endogenous variables, the identification of structural shocks through economically grounded restrictions, and the estimation of impulse responses that trace the dynamic propagation of shocks over time. As a result, VAR-based approaches have emerged as the dominant empirical strategy for analyzing the macroeconomic effects of supply disruptions and external shocks.

This paper develops a structural framework to study the non-monotonic effects of global supply chain disruptions on industrialization in Small Open Economies, with a particular focus on Africa. We depart from standard linear propagation models by embedding global shocks into a multi-sector production system with input com-

plementarities and cross-sector linkages. Building on the "weak link" logic of Jones (2011) and the network propagation framework of Acemoglu et al. (2012), we model industrial production as a CES function with imperfect substitutability across inputs and an explicit dependence on both contemporaneous imported materials and lagged agricultural output. Imported inputs are further differentiated by origin following the Armington (1969) structure, consistent with the global value chain literature (Boehm et al. 2019, Oberfield 2021). This setup generates a novel three-wave transmission mechanism: an immediate contraction driven by material shortages, a delayed "Agro-Industrial Echo" operating through upstream agricultural dependencies, and a persistent hysteresis effect arising from disrupted capital accumulation. The interaction of these channels produces a W-shaped industrial recovery path. Crucially, we introduce intra-African trade as a structural substitution buffer, governed by the regional sourcing share, which attenuates each transmission channel, especially the lagged agricultural propagation, thereby linking regional integration directly to macroeconomic resilience.

To empirically evaluate these mechanisms, we adopt a hybrid identification strategy. We first estimate a block heterogeneous panel SVAR pioneered by Pedroni (2013) on a sample of 14 African economies over 2000 to 2026. The use of a panel SVAR is particularly well-suited to the short time dimension of African macro data, as it allows us to exploit cross-country heterogeneity while imposing economically meaningful short-run restrictions to identify exogenous global supply chain shocks. However, standard SVAR impulse responses impose a rigid, exponentially decaying structure that is ill-suited to capturing the non-monotonic dynamics predicted by our model. We therefore complement SVAR with Local Projections (LP) popularized by Jordà (2005), which provide flexible horizon-by-horizon estimates and allow us to directly test the presence of W-shaped recovery patterns. We extend this literature by introducing an instrumental variable strategy to identify the causal role of intra-African trade. Specifically, we address potential endogeneity concerns by instrumenting regional trade shares using a shift-share (Bartik) design with multiple instruments. We construct three alternative instruments, one de facto (Operational) and two de jure (Legal and Policy), based on granular AfCFTA implementation markers: Guided Trade Initiative activity, cumulative ratification counts, and legislated tariff phase-down schedules, respectively. By interacting these continental policy shifts with pre-determined maritime connectivity (LSCI), we aim to isolate variation in regional integration that is plausibly exogenous to contemporaneous industrial dynamics. This strategy allows us to assess how trade integration shapes the dynamic response to global supply chain shocks, with results providing evidence consistent with the role of regional trade integration as a mitigating factor in the transmission of global shocks.

A growing literature uses structural VAR approaches to identify and quantify the macroeconomic effects of global supply chain (GSC) disruptions. Using sign-restricted VARs, Celasun et al. (2022) attribute roughly half of the surge in euro area manufacturing producer price inflation in 2021 to supply bottlenecks, while Finck & Tillmann (2022) combine narrative and sign restrictions to show that GSC shocks reduce indus-

trial production and raise consumer prices, with shocks originating in China having the largest effects. Similarly, Kuehl et al. (2022) distinguish between supply and demand drivers of delivery delays during the Covid-19 pandemic and find that while demand pressures explain congestion, supply-side disruptions play a central role in price dynamics. Focusing on trade frictions, Kilian et al. (2021) document that container shipping constraints significantly contributed to the incomplete post-pandemic recovery in the United States. More recently, Kemp et al. (2023) combine Bayesian VAR techniques with local projections to show that supply disruptions reduced global value added and increased inflation during the 2021 recovery. Other authors have also analyzed macroeconomic consequences of supply chain disruptions and trade collapse (Bems et al. 2010, Boehm et al. 2019, Finck & Tillmann 2022).

Despite these advances, the existing literature remains largely focused on advanced economies and typically relies on linear or monotonic dynamics. They do not allow for sectoral lag structures or regional substitution mechanisms. In addition, evidence for Africa is extremely limited. To the best of our knowledge, Andriantomanga et al. (2022) is among the very few works that provide systematic analysis of GSC disruptions in Sub-Saharan Africa. Although he does better by using a panel local projection framework, he only focuses on inflation. Thus, he does not provide any further analysis of the heterogeneity in countries response. As a result, the mechanisms through which global disruptions affect industrialization in African economies, and whether these effects are non-linear or amplified over time, remain largely unexplored.

Therefore, this paper makes four contributions. First, we develop a structural framework that generates a three-wave propagation mechanism (through materials, agro-industrial linkages, and capital accumulation), yielding W-shaped industrial dynamics following global supply chain shocks. Second, we show that intra-African trade acts as a structural buffer that attenuates these transmission channels. Third, we combine a panel SVAR with Local Projections to identify and estimate non-monotonic impulse responses. Finally, we provide causal evidence using an AfCFTA-based instrument for regional trade integration.

The rest of the paper is structured as follows: The section 2 set up a theoretical model to discipline our empirical investigations. The section 3 unpacks our empirical strategy and presents the data. The section 4 analyzes the results of the SVAR and LP models estimation. The section 5 analyzes the shape of the dynamics of responses and the role of intra-African trade. Section 6 comes with some concluding remarks and policy recommendations.

2 The model

Our modeling strategy deliberately adopts a parsimonious decentralized equilibrium framework that embeds sectoral production linkages, imported input dependence, and origin-based substitution without imposing a fully quantitative general equilibrium structure. The objective is not to provide a complete welfare analysis, but to isolate the key propagation mechanisms through which global supply chain disruptions affect

industrial dynamics in developing economies. In particular, the use of CES technologies with input complementarity allows us to capture amplification effects emphasized in the production network literature, while the origin-differentiated import structure introduces a tractable margin for regional substitution. This parsimonious approach ensures analytical transparency and delivers sharp, testable implications, most notably the emergence of multi-phase (W-shaped) adjustment dynamics and the role of intra-regional trade as a resilience mechanism, while leaving quantitative calibration and welfare analysis to future work.

2.1 The agricultural sector

We start our model with an agricultural production function under the assumption that agriculture provides the main upstream inputs to manufacturing. Agricultural output $Y_{A,t}$ depends on labor $L_{A,t}$, land T_t, agricultural total factor productivity $A_{A,t}$, capital $K_{A,t}$, and fertilizers X_t. We adopt a CES structure that allows for substitutability between primary factors and complementarity between these factors and modern intermediate inputs:

$$Y_{A,t} = A_{A,t} T_t^{\theta} \left[\omega \left(L_{A,t}^{\gamma} K_{A,t}^{1-\gamma} \right)^{\frac{\sigma_A - 1}{\sigma_A}} + (1-\omega) X_t^{\frac{\sigma_A - 1}{\sigma_A}} \right]^{\frac{\sigma_A}{\sigma_A - 1}} \tag{1}$$

The fertilizer bundle combines domestic and imported varieties according to

$$X_t = \left[\phi X_{D,t}^{\rho_A} + (1-\phi)(\Lambda(S_t) X_{I,t})^{\rho_A} \right]^{1/\rho_A}. \tag{2}$$

Here, $X_{D,t}$ and $X_{I,t}$ denote domestic and imported fertilizers, respectively. The parameter σ_A is the elasticity of substitution between the primary factor bundle and the fertilizer bundle. We assume $\sigma_A < 1$ to reflect complementarity between modern agricultural inputs and traditional factors.[1] The term $\Lambda(S_t) \in (0,1)$ is a global supply chain (GSC) filter that captures disruptions affecting imported fertilizers.

2.2 The industrial sector

Following Boehm et al. (2019) and Oberfield & Raval (2021), we depart from a pure Cobb-Douglas specification and adopt a CES production structure with $\sigma_M < 1$. This reflects the fact that in manufacturing, especially in import-dependent developing economies, intermediate inputs and productive factors are gross complements. As Jones (2011) shows, such "weak links" can generate more-than-proportionate output losses when one critical input is disrupted. Manufacturing output depends on labor $L_{M,t}$, capital $K_{M,t}$, materials M_t, and manufacturing total factor productivity $A_{M,t}$. We also assume that current industrial production depends on lagged agricultural output $Y_{A,t-1}$:

$$Y_{M,t} = A_{M,t} \left[\alpha L_{M,t}^{\frac{\sigma_M - 1}{\sigma_M}} + \beta K_{M,t}^{\frac{\sigma_M - 1}{\sigma_M}} + \delta \left(M_t^{\gamma} Y_{A,t-1}^{1-\gamma} \right)^{\frac{\sigma_M - 1}{\sigma_M}} \right]^{\frac{\sigma_M}{\sigma_M - 1}}. \tag{3}$$

[1] Foster & Rosenzweig (2010) emphasizes that modern inputs are often complementary to land and other primary factors in low-income agricultural systems.

The parameter δ captures the weight of intermediate inputs relative to labor and capital. The parameter $\gamma \in (0,1)$ governs the agro-industrial composition of the intermediate bundle.[2] The material bundle is itself a CES aggregate of domestic and imported intermediates:

$$M_t = \left[\varphi M_{D,t}^{\rho_M} + (1-\varphi)(\Phi(S_t)M_{I,t})^{\rho_M}\right]^{1/\rho_M}. \tag{4}$$

Here, φ is the domestic material share parameter and $\Phi(S_t) \in (0,1)$ captures disruptions affecting imported materials. This block delivers the *Wave 1* channel, namely the contemporaneous industrial effect of imported input shortages. The dependence of (3) on $Y_{A,t-1}$ delivers the *Wave 2* channel, through which earlier shocks to agricultural inputs affect current industrial production. To capture the dependence of African industry on foreign machinery, we write manufacturing capital accumulation as

$$K_{M,t} = (1-\delta_k)K_{M,t-1} + \left[\theta I_{D,t-k}^{\rho_K} + (1-\theta)(\Psi(S_{t-k})I_{I,t-k})^{\rho_K}\right]^{1/\rho_K}, \tag{5}$$

where $I_{D,t-k}$ denotes domestic investment goods, $I_{I,t-k}$ denotes imported machinery, and $\Psi(S_{t-k}) \in (0,1)$ is the GSC filter affecting foreign equipment. This equation captures the *Wave 3* channel, namely the delayed impact of supply disruptions on industrial capital accumulation.

2.3 The sector of services

Services are produced using labor and capital, but their productivity also depends on manufacturing activity:

$$Y_{S,t} = A_{S,t}L_{S,t}^{\phi}K_{S,t}^{1-\phi} \cdot (Y_{M,t})^{\psi}. \tag{6}$$

The parameter ψ captures the dependence of services on industrial activity through transport, insurance, distribution, and related activities. Since the focus of the paper is on industry, we do not develop this indirect wave further.

2.4 A decentralized equilibrium

To place these sectoral mechanisms in a standard macroeconomic environment, we close the model with a representative household and competitive firms. The household chooses consumption C_t, investment I_t, and labor supply L_t to maximize lifetime utility

$$\max_{\{C_t,I_t,L_t\}} \sum_{t=0}^{\infty} \beta^t \left[\log C_t - \chi \frac{L_t^{1+\varphi_L}}{1+\varphi_L}\right] \tag{7}$$

subject to the budget constraint

$$C_t + I_t = w_t L_t + r_t K_{t-1} + \Pi_t \tag{8}$$

[2] For branches such as iron and steel, non-ferrous metals, petroleum, chemicals, rubber, or plastic products, one can think of γ as being close to one.

and the law of motion of aggregate capital

$$K_t = (1 - \delta_K)K_{t-1} + I_t. \tag{9}$$

The household first-order conditions imply the standard Euler equation

$$\frac{1}{C_t} = \beta E_t \left[\frac{1}{C_{t+1}} (r_{t+1} + 1 - \delta_K) \right] \tag{10}$$

and the labor supply condition

$$\chi L_t^{\varphi_L} = \frac{w_t}{C_t}. \tag{11}$$

Agricultural and manufacturing firms take prices as given and choose inputs to maximize profits. The manufacturing firm solves

$$\max_{L_{M,t}, K_{M,t}, Z_t} \; P_{M,t} Y_{M,t} - w_t L_{M,t} - r_t K_{M,t} - P_{Z,t} Z_t, \tag{12}$$

with $Y_{M,t}$ given by (3). Under perfect competition, factor prices equal marginal products:

$$w_t = P_{M,t} \frac{\partial Y_{M,t}}{\partial L_{M,t}}, \qquad r_t = P_{M,t} \frac{\partial Y_{M,t}}{\partial K_{M,t}}, \qquad P_{Z,t} = P_{M,t} \frac{\partial Y_{M,t}}{\partial Z_t}. \tag{13}$$

Detailed derivations of household and firm optimality conditions, as well as the import allocation system, are provided in Appendix A.

2.5 The Substitution Buffer: Intra-African Trade

We model the imported component of any intermediate input $Z \in \{M, X, I\}$ as a CES aggregation of intra-African and extra-continental sources:

$$Z_{I,t} = \left[\nu_t (\Gamma_R(S_t) Z_{R,t})^{\frac{\sigma_R - 1}{\sigma_R}} + (1 - \nu_t)(\Gamma_E(S_t) Z_{E,t})^{\frac{\sigma_R - 1}{\sigma_R}} \right]^{\frac{\sigma_R}{\sigma_R - 1}}. \tag{14}$$

Here, $Z_{R,t}$ and $Z_{E,t}$ denote regional and extra-continental inputs, respectively. The parameter $\nu_t \in (0, 1)$ captures the share of intra-African sourcing, while $\sigma_R > 0$ governs the elasticity of substitution across origins. The terms $\Gamma_R(S_t)$ and $\Gamma_E(S_t)$ are origin-specific iceberg filters, with regional channels assumed to be more resilient than extra-continental ones. Cost minimization yields the sourcing condition

$$\frac{Z_{E,t}}{Z_{R,t}} = \frac{1 - \nu_t}{\nu_t} \left(\frac{P_{E,t}/\Gamma_E(S_t)}{P_{R,t}/\Gamma_R(S_t)} \right)^{-\sigma_R}, \tag{15}$$

showing that deeper regional integration and greater substitution capacity both reduce exposure to extra-continental disruptions. The corresponding dual price index for imported inputs is

$$P_{Z_I,t} = \left[\nu_t P_{R,t}^{1-\sigma_R} + (1 - \nu_t) \left(\frac{P_{E,t}}{\Gamma_E(S_t)} \right)^{1-\sigma_R} \right]^{\frac{1}{1-\sigma_R}}. \tag{16}$$

This block introduces the *Substitution Buffer*: when global sourcing becomes more costly or constrained, firms reallocate demand toward intra-African suppliers. The strength of this buffer depends jointly on the regional sourcing share ν_t and the substitution elasticity σ_R.

2.6 Industrial Dynamics under Global Supply Chain Shocks

Combining the previous blocks, the manufacturing production function can be rewritten as

$$Y_{M,t} = A_{M,t}\left[\alpha L_{M,t}^{\frac{\sigma_M-1}{\sigma_M}} + \beta K_{M,t}^{\frac{\sigma_M-1}{\sigma_M}} + \delta\left((M_{D,t}+\Phi(S_t)M_{I,t})^{\gamma}\cdot Y_{A,t-1}^{1-\gamma}\right)^{\frac{\sigma_M-1}{\sigma_M}}\right]^{\frac{\sigma_M}{\sigma_M-1}}. \tag{17}$$

This structure generates a multi-stage propagation of global shocks.

Proposition 1 (Wave 1). *A negative GSC shock at time t, reducing $\Phi(S_t)$, leads to an immediate decline in manufacturing output.*

Proof. Effective materials are given by $M_{D,t} + \Phi(S_t)M_{I,t}$. Since $\Phi'(S_t) < 0$, a rise in the shock reduces the availability of imported materials. Given $\sigma_M < 1$, inputs are complements, so this reduction lowers the marginal productivity of all factors and decreases $Y_{M,t}$. □

Proposition 2 (Wave 2). *A GSC shock at time $t-1$ reduces agricultural output $Y_{A,t-1}$, generating a delayed decline in manufacturing output at time t.*

Proof. Agricultural production depends on effective fertilizers $X_{D,t-1}+\Lambda(S_{t-1})X_{I,t-1}$, with $\Lambda'(S_{t-1}) < 0$. A shock therefore lowers $Y_{A,t-1}$. Since the composite input is $Z_t = M_t^{\gamma}Y_{A,t-1}^{1-\gamma}$, a reduction in lagged agricultural output lowers Z_t and thus $Y_{M,t}$. □

Proposition 3 (Wave 3). *A GSC shock reduces imported capital goods, generating a persistent decline in manufacturing output through capital accumulation.*

Proof. Capital evolves according to $K_{M,t} = (1-\delta_K)K_{M,t-1} + I_{D,t-1} + \Psi(S_{t-1})I_{I,t-1}$, with $\Psi'(S_{t-1}) < 0$. A shock lowers effective imported investment and therefore future capital stock. Since output is increasing in capital, manufacturing output declines persistently over time. □

Taken together, these mechanisms imply that industrial dynamics following a GSC shock are characterized by a W-shaped adjustment path: Wave 1 generates an immediate contraction through materials; Wave 2 produces a delayed contraction via agricultural linkages; and Wave 3 induces a persistent slowdown through capital accumulation.

2.6.1 The role of regional integration

We now characterize the resilience role of intra-African trade.

Proposition 4 (Absence of buffer). *As $\nu_t \to 0$, the industrial sector becomes fully exposed to global supply chain shocks:*

$$\lim_{\nu_t\to 0}\frac{\partial Y_{M,t}}{\partial S_t} = \left.\frac{\partial Y_{M,t}}{\partial S_t}\right|_{global}. \tag{18}$$

Proof. When $\nu_t \to 0$, the CES import aggregator collapses to extra-continental sourcing, so imported inputs fully inherit the global shock. Since manufacturing depends positively on these imported inputs, the transmission of shocks is maximal. □

Proposition 5 (Full regional buffer). *As $\nu_t \to 1$, the economy becomes insulated from global supply chain shocks:*

$$\lim_{\nu_t \to 1} \frac{\partial Y_{M,t}}{\partial S_t} = 0. \tag{19}$$

Proof. When $\nu_t \to 1$, the import aggregator converges to regional sourcing, which is independent of extra-continental disruptions. Global shocks therefore cease to affect the effective input bundle used in production, and the response of manufacturing output vanishes. □

These limits characterize intra-African trade as a *Substitution Buffer*. When ν_t is low, the three-wave mechanism operates without attenuation and generates a pronounced W-shaped industrial response. As ν_t rises, substitution toward regional inputs weakens each transmission channel, especially the agro-industrial linkage underlying Wave 2. In the limit $\nu_t \to 1$, the propagation of GSC shocks is fully neutralized and the W-shaped path collapses into a smooth, shock-invariant trajectory.

2.7 Theoretical Impulse Response Functions (IRF)

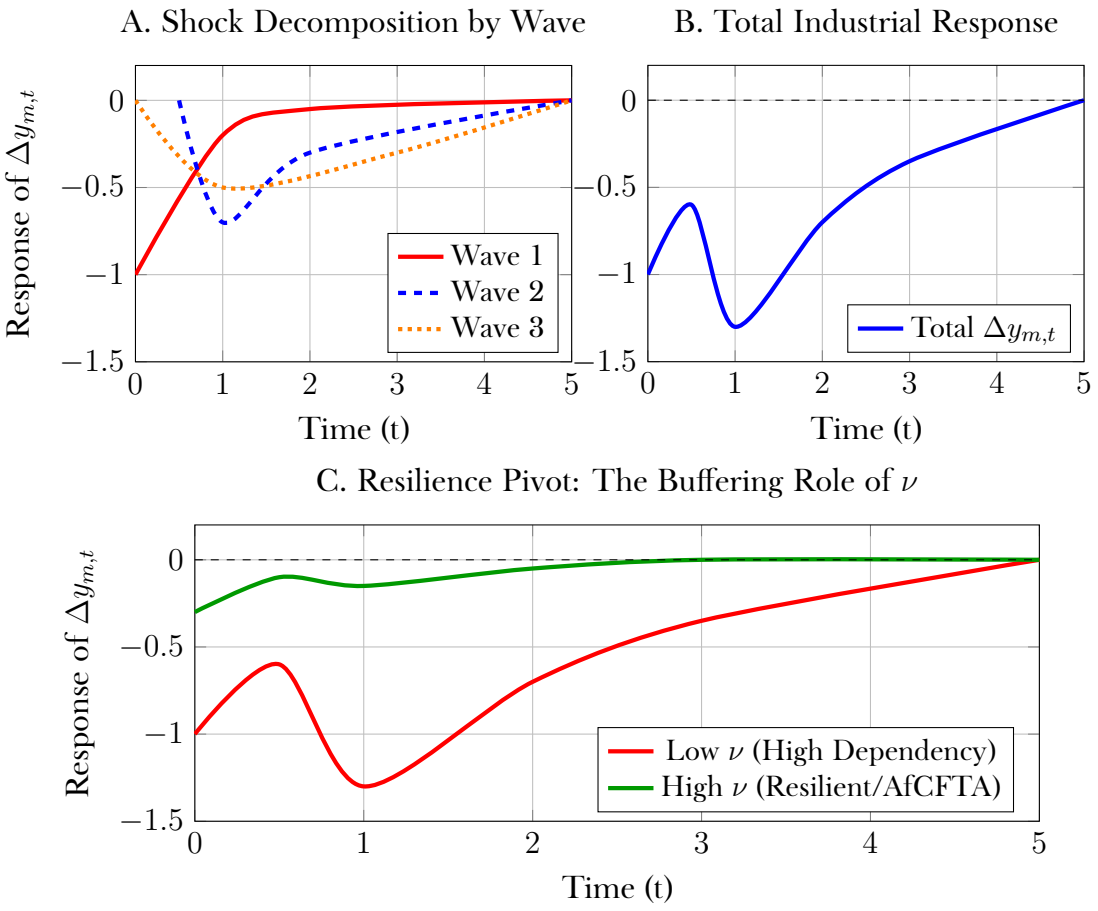


Figure 1: Panel A decomposes the response of manufacturing output into three channels: contemporaneous materials (Wave 1), lagged agro-industrial linkages (Wave 2), and capital accumulation (Wave 3). Panel B shows the resulting W-shaped recovery driven by the staggered propagation of these effects. Panel C illustrates the buffering role of intra-African sourcing (ν): higher regional integration attenuates all channels, especially the lagged agricultural transmission, and flattens the W-shaped response.

3 Empirical Strategy

This section takes the model to the data. Our theoretical model delivers three sharp predictions: global supply chain (GSC) disruptions generate a non-monotonic response of manufacturing output, combining an immediate contraction, a delayed secondary downturn, and a persistent recovery phase (Propositions 1 to 3); the delayed component operates through agro-industrial linkages, implying a lagged second trough; and the magnitude of these effects depends on intra-African trade integration, with higher regional sourcing attenuating shock propagation.

To test these predictions, we adopt a hybrid identification strategy combining a block heterogeneous panel Structural Vector Autoregression (SVAR) with Local Projections (LP). The SVAR is used to identify exogenous GSC shocks through economically motivated restrictions, while LP flexibly estimates impulse responses without

imposing VAR dynamics. This combination is particularly suited to our setting, as it allows us to capture the non-linear and multi-phase adjustment patterns predicted by the model.

3.1 Step 1: Structural Identification of GSC shock

Given that

GSCPI is a reduced-form variable, not a structural shock. GSCPI is what you observe; it reflects the joint outcome of every shock hitting the global supply chain network (supply chain shocks proper, but also demand pressures (a global demand boom strains shipping capacity and pushes GSCPI up), monetary surprises that move freight rates, and so on). To extract the structural GSC shock, which is one of the components driving GSCPI, we need an external instrument which is correlated with GSCPI's reduced-form residual but exogenous to the other structural shocks.

To get a variation of our GSC structural shock which is by construction independent of how GSCPI movement, Second, we code the events with sign and magnitude based on documented physical disruption port-days lost and shipping capacity offline within a quarter

We first specify a Panel SVAR to perform **Structural Decomposition**. Given that African nations are small open economies (SOEs), we adopt a variant of panel SVAR suggested by Pedroni (2013) by imposing a block-exogeneity restriction where global dynamics are independent of domestic idiosyncratic shocks. The detail of our structural decomposition are presented as follows:

The Structural and Reduced-Form Panel VAR Framework

We begin by representing the economy in its structural form to explicitly define the contemporaneous relationships between variables. Let ΔZ_{it} be a vector of endogenous variables for country i at time t. We partition this vector into two blocks:

$$A_i(L)\Delta Z_{it} = \varepsilon_{it} \tag{20}$$

where $A_i(L)$ is a polynomial matrix of structural parameters and ε_{it} is a vector of structural shocks. The system is partitioned as:

$$\begin{bmatrix} A_{11}(L) & 0 \\ A_{21}(L) & A_{22,i}(L) \end{bmatrix} \begin{bmatrix} \Delta X_t^{Global} \\ \Delta Y_{it}^{Local} \end{bmatrix} = \begin{bmatrix} \varepsilon_t^{Global} \\ \varepsilon_{it}^{Local} \end{bmatrix} \tag{21}$$

The **Global Tier** (ΔX_t^{Global}) captures world-level dynamics and includes the Global Supply Chain Pressure Index (GSCPI), World GDP, and Global CPI. The **Local Tier** (ΔY_{it}^{Local}) contains the country-specific manufacturing growth rate.

We impose a **Block-Exogeneity Assumption** by setting the upper-right block of the parameter matrix to zero. This restriction enforces the Small Open Economy (SOE) assumption, implying that while global shocks impact African economies, idiosyncratic shocks within individual African nations (e.g., domestic policy shifts) have

no feedback effect on global supply chain equilibria or world prices. This methodology aligns with recent high-impact applications in emerging market macroeconomics (Ha et al. 2019, Bhattacharya et al. 2018, Hernaiz et al. 2018).
For each country i in our panel, we estimate the following reduced-form Vector Autoregression (VAR):

$$\Delta Z_{it} = \mu_i + \sum_{j=1}^{p_i} \Gamma_{i,j} \Delta Z_{i,t-j} + u_{it} \tag{22}$$

where ΔZ_{it} is a 4×1 vector of endogenous variables $[\Delta X_t^{Global}, \Delta y_{it}^{Local}]'$. The vector u_{it} represents the reduced-form innovations with covariance matrix $E[u_{it}u_{it}'] = \Omega_i$. Then, to capture the dynamic impact of shocks over time, we invert the VAR into its **Vector Moving Average (VMA)** representation:

$$\Delta Z_{it} = F_i(L)u_{it} = \sum_{j=0}^{\infty} F_{i,j} u_{i,t-j} \tag{23}$$

where $F_{i,j}$ are the matrices of reduced-form impulse responses that track how a change in the residual u affects the system at horizon j.

Structural Identification: Short-Run Restrictions

While long-run restrictions are often utilized to isolate permanent supply shifts, they are susceptible to small-sample bias and the "zero-frequency" problem (Sarte 1997). Similarly, sign restrictions remain problematic for a heterogeneous panel, where a single structural innovation may trigger divergent directional responses across varying national trade structures (Arias et al. 2018). We therefore employ a recursive Cholesky identification strategy based on **short-run zero restrictions**.

This approach is theoretically grounded in the informational delay and physical rigidity hypotheses: global logistics and maritime constraints are physically sticky and do not respond contemporaneously to innovations in aggregate demand or nominal prices within a single quarter (Christiano et al. 2005). Consequently, we assume a linear mapping between reduced-form residuals and structural shocks, $u_{it} = A_{i,0}\varepsilon_{it}$, where the impact matrix $A_{i,0}$ is identified via a lower-triangular Cholesky factorization of the contemporaneous covariance matrix. The variables are ordered as $Z_t = [GSCPI_t, GDP_t, CPI_t, \Delta y_{m,it}]'$, which implies that the **Global Supply Chain Shock** ($\varepsilon_t^{S_GSC}$) is the most exogenous innovation in the system. The recursive structure is defined as follows:

$$\begin{bmatrix} u_t^{GSCPI} \\ u_t^{GDP} \\ u_t^{CPI} \\ u_{it}^{Indus} \end{bmatrix} = \begin{bmatrix} a_{11} & 0 & 0 & 0 \\ a_{21} & a_{22} & 0 & 0 \\ a_{31} & a_{32} & a_{33} & 0 \\ a_{41} & a_{42} & a_{43} & a_{44,i} \end{bmatrix} \begin{bmatrix} \varepsilon_t^{S_GSC} \\ \varepsilon_t^{D_Global} \\ \varepsilon_t^{Infl} \\ \varepsilon_{it}^{Local} \end{bmatrix} \tag{24}$$

This identification scheme allows us to isolate the primitive supply chain shock from global demand fluctuations and nominal price innovations. By substituting the identi-

fied $A_{i,0}$ into the Vector Moving Average (VMA) representation, we derive the **Structural Impulse Response Functions (SIRFs)**:

$$Z_{it} = \sum_{j=0}^{\infty} \Theta_{i,j} \varepsilon_{i,t-j} \tag{25}$$

where $\Theta_{i,j} = F_{i,j} A_{i,0}$ quantifies the dynamic response of the African industrial sector to a one-standard-deviation structural innovation in global supply chain pressure.

3.2 Data and Pre-Estimation Tests

3.2.1 Variables and some descriptive analysis

This study uses a panel dataset of 14[3] in African economies covering the period 2000 to 2026, integrating global macroeconomic indicators with sector-specific industrial data for African economies. To measure global logistics disruptions, we utilize the Global Supply Chain Pressure Index (GSCPI) developed by the Federal Reserve Bank of New York which the methodology was pioneered by Benigno et al. (2022). This index captures global supply constraints by aggregating cross-border transportation costs and manufacturing supply chain variables into a common factor. While Benigno et al. (2022) attempt to purge demand effects from the GSCPI, empirical evidence (Ferrari 2022, Lu et al. 2021) suggest that residual demand components may remain, particularly through inventory-amplification channels. We retrieve World GDP (constant 2015 USD) and the World GDP Deflator from the World Bank's World Development Indicators (WDI). The dependent variable is Total Industrial Value Added (annual growth rate), also sourced from the WDI, which captures a broad spectrum of industrial activity, including manufacturing, agro-industry, mining, and utilities, essential for a holistic view of African structural dynamics.

The dual-panel visualization displayed in the figure 2[4] below provides compelling preliminary evidence of a co-movement between GSC fluctuation and industrialization dynamic. I also support the non-monotonic structural response of African industry to global shocks. The left panel, which overlays the standardized Global Supply

[3] The 14 african countries that make up our sample are those for which long sufficient quarterly data series on industrial production are available

[4] To ensure the statistical integrity of the comparative analysis, several technical transformations were applied to the panel data. First, all series in the left panel were standardized to Z-scores (zero-mean and unit-variance). This step is mathematically essential to eliminate scale disparities between the GSCPI (a global index) and industrial growth rates (percentages), thereby allowing for a direct comparison of their relative fluctuations. Second, for the cross-correlation analysis in the right panel, we applied a Hodrick-Prescott (HP) filter with a smoothing parameter of $\lambda = 1600$ to extract the cyclical components of the quarterly series. By isolating the cycles from long-term trends, we ensure that the identified linkages represent true short-to-medium-term macroeconomic dependencies rather than coincidental secular drifts. The inclusion of the 95% Panel Confidence Interval (shaded area) further accounts for the cross-sectional heterogeneity across the 14 sample countries, confirming that the observed fluctuations represent a systemic continental trend. Together, these diagnostics verify that the data are stationary and exhibit the structural "memory" required to proceed with the impulse response analysis of global-local shock transmission.

Chain Pressure Index (GSCPI) with the African industrial growth mean, illustrates a high degree of historical synchronization. We observe that major escalations in global supply chain stress are consistently met with immediate, visible contractions in regional industrial output, a phenomenon we define as the "Material Rupture." Complementing this, the right panel presents the cross-correlation function (CCF) of the cyclical components, which offers a statistical "skeleton" of the hypothesized W-shape. Specifically, the emergence of a secondary negative correlation peak at the 10-quarter horizon ($h = 10$) provides a non-parametric validation of the Agro-Industrial Echo. This suggests that the initial supply-side shock propagates through a second, lagged channel of agricultural input depletion, effectively creating a secondary trough in the industrial cycle. While these diagnostic patterns are suggestive of a multi-phase adjustment, the precise magnitude, persistence, and structural shape of these effects will be formally uncovered through the SVAR-Local Projections (SVAR-LP) framework implemented in the following section.

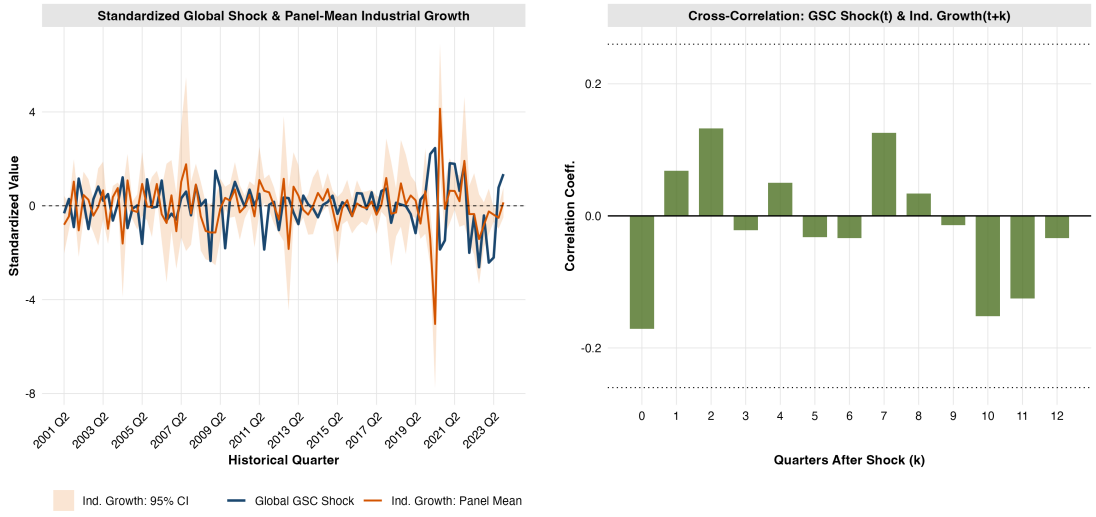


Figure 2: GSC, industrialization series and cross-correlation coefficient
Source: Author's own estimations

3.2.2 Stationary tests and lag selection

To ensure the validity of our SVAR and Local Projection frameworks, we rigorously test the integration properties of both our time series (first tier) and our panel time series (second tier) variables using confirmatory analysis approaches. For the time series, we employ two complementary unit root tests: the Augmented Dickey-Fuller (ADF) and the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) tests. As displayed in table 1 bellow, the ADF test rejects the null hypothesis of a unit root ($p < 0.05$) and ($p < 0.01$) respectively, while the KPSS test fails to reject the null of stationarity ($p = 0.1$) for World GDP Growth and Global Inflation. Similarly, for Delta GSCPI, the ADF test rejects the unit root at the 10% significance level, supported by a KPSS result that fails to reject stationarity. Since both tests, which operate under opposing null hypotheses, converge on the same result, we can robustly conclude that all three global variables are stationary in levels, or $I(0)$. This validates their use in the subsequent Structural

Vector Autoregression (SVAR) model without the risk of spurious correlations.

While the Hadri and KPSS tests suggest some persistence in the quarterly series,

Table 1: Confirmatory Stationarity Analysis

Variable	Test	H0	H1	Statistic
Global Variables				
World GDP Gr	ADF	Unit Root	Stationary	-4.823**
World GDP Gr	KPSS	Stationary	Unit Root	0.045
Global Inflation	ADF	Unit Root	Stationary	-2.686
Global Inflation	KPSS	Stationary	Unit Root	0.410*
Delta GSCPI	ADF	Unit Root	Stationary	-4.395**
Delta GSCPI	KPSS	Stationary	Unit Root	0.046
Panel Variable				
Industrial Growth	IPS	All Unit Root	Some Stationary	-27.045***
Industrial Growth	Hadri	Stationary	Unit Root	-1.369

*Note: p<0.01***, p<0.05**, p<0.1**

likely due to the high volatility of industrial production in emerging markets, the ADF and IPS tests strongly reject the presence of a unit root at the 1% level. Consequently, the variables are treated as stationary $I(0)$ for the SVAR estimation, with the observed persistence to be captured by the optimal lag structure of the model. We follow the consensus in macro-panel literature (Im et al. 2003, Pesaran 2007) according to which the IPS test is superior to Hadri one because it allows for this heterogeneity.

Optimal lag length for the Tier 1 VAR was determined using a consensus of information criteria. While the AIC suggests a deeper structure, the Schwarz (BIC) and Hannan-Quinn (HQ) criteria favor a more parsimonious specification to preserve degrees of freedom. Consequently, a lag order of p=2 was selected. This choice captures the necessary transmission dynamics of quarterly data while preventing overparameterization, ensuring the statistical power required for the subsequent Local Projection identification. The details for lag selection are presented in table x in appendix.

3.3 Stage I: Estimation and Impulse Response Functions

In the first stage, we estimate the system using a country-by-country OLS approach to extract idiosyncratic coefficients, thereby avoiding the "pooling bias" that often obscures diverse structural realities in African industry.

To account for potential heteroskedasticity and the small-sample properties of our panel, we calculate the 95% confidence intervals for the **Impulse Response Functions (IRFs)** using 1,000 iterations of a *wild bootstrap*. This allows us to map the "Three Waves" of GSC shocks: the immediate material shock, the lagged agro-industrial echo, and the capital gestation gap.

3.4 Step 2: Response Mapping via Local Projections (LP)

While the SVAR is optimal for identifying structural shocks, its internal autoregressive structure often "smooths" impulse responses, potentially obscuring the hypothesized "W-shaped" hypothesis we seeking to test. To capture these non-monotonicities, we take the identified structural shock $\hat{\varepsilon}_t^{S\text{-}GSC}$ from Step 1 and estimate the response of manufacturing growth ($\Delta y_{m,it}$) using the Local Projections method of Jordà (2005):

$$y_{i,t+h} - y_{i,t-1} = \alpha_{i,h} + \beta_h \hat{\varepsilon}_t^{S\text{-}GSC} + \sum_{j=1}^{p} \gamma_{h,j} \Delta Z_{i,t-j} + \xi_{i,t+h} \tag{26}$$

Where:

- β_h: Represents the Impulse Response Function (IRF) at horizon h. Unlike SVAR-based IRFs, β_h is estimated independently for each year, allowing the data to manifest multiple troughs without functional form constraints.
- $\alpha_{i,h}$: Country-fixed effects to account for time-invariant heterogeneity in industrial structures.
- $\Delta Z_{i,t-j}$: A vector of control lags to ensure the shock is strictly exogenous to past local and global conditions.

This hybrid approach ensures that our findings are grounded in structural theory (via the SVAR filter) while remaining empirically flexible enough to detect the "Echo" and "Hysteresis" waves (via the LP lens). In addition, the Local Projection analysis serves to check the robustness of our SVAR results given that the two approaches yield to the same impulse response functions when the model is linear in variables and includes sufficient lags(Plagborg-Møller & Wolf 2021).

Details on the testing of the W-shaped response dynamics and the role of intra-African trade are provided in Section 5.

4 Baseline Results: Dynamic Industrial Responses to GSC Shocks

4.1 Block Exogenous SVAR Evidence

Figure 7 reports the impulse responses of industrial production growth to global shocks. The results indicate that African industrial activity is highly sensitive to global supply chain disruptions. A one standard deviation increase in the Global Supply Chain Pressure Index (GSCPI) leads to an immediate decline in industrial growth of approximately 0.08 units on impact ($t = 0$). The median response gradually returns to baseline within four quarters. However, substantial heterogeneity emerges across countries: the lower quartile remains below baseline for up to eight quarters, indicating more persistent effects in relatively vulnerable economies.

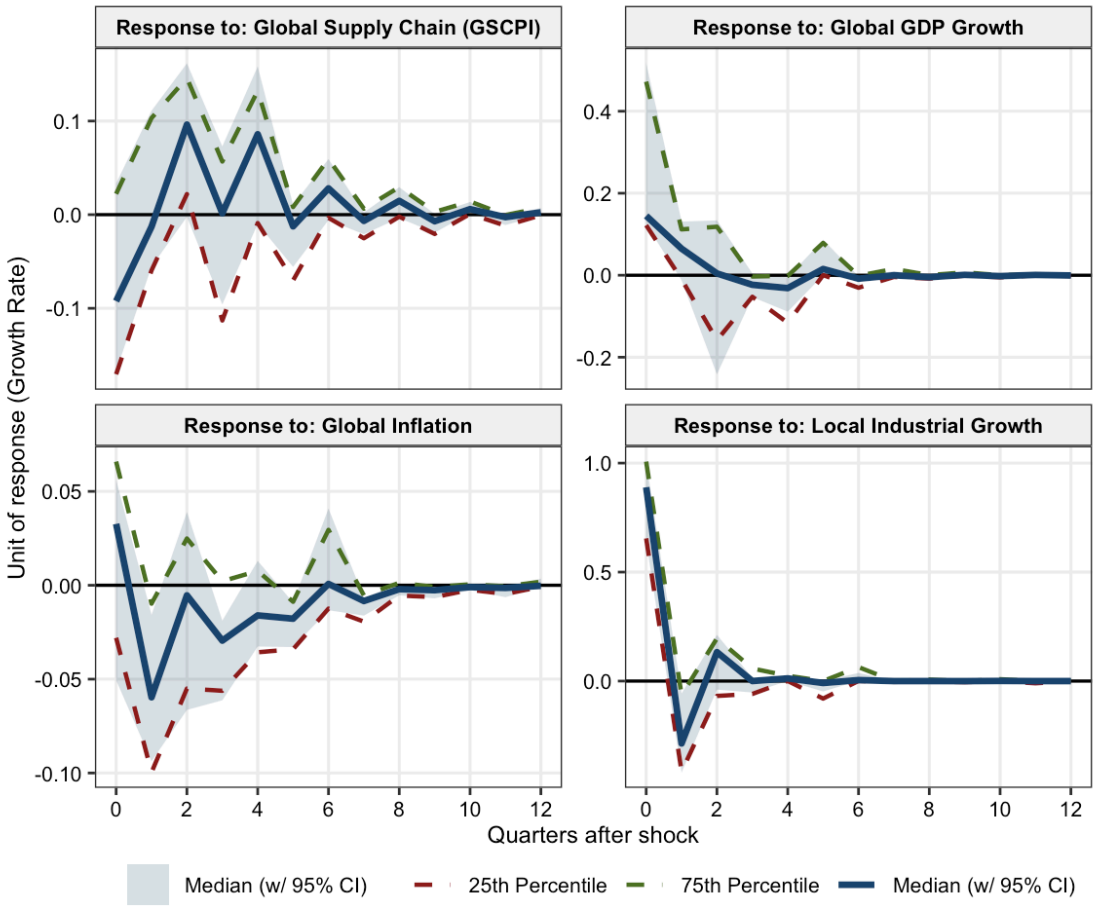


Figure 3: Countries' industrial production growth rate response to each global structural shock

Note: Differences between median, 25th, and 75th percentile responses reflect cross-country heterogeneity. Country-specific impulse responses are reported in the appendix.

Source: Author's own estimations

While the W-shaped dynamics are more clearly identified using Local Projections, the SVAR responses already provide suggestive evidence of non-monotonic adjustment. In particular, the inflation response exhibits an initial decline, followed by a short-lived rebound and a subsequent secondary contraction before stabilizing. This pattern is consistent with a multi-stage transmission mechanism, although it remains less pronounced in industrial growth at this stage. The cumulative impulse responses, reported in Figure 4, further highlight substantial cross-country heterogeneity. The median cumulative response suggests partial recovery by horizon $h = 12$. However, the lower quartile displays persistent negative deviations, stabilizing around -0.4 standard deviations. This indicates that for a subset of countries, supply chain disruptions are associated with long-lasting reductions in industrial activity. In contrast, the upper quartile exhibits a positive cumulative response in the longer run, suggesting that more resilient economies partially offset the initial shock. Overall, the dispersion between quantiles indicates that global supply chain disruptions contribute not only to aggregate fluctuations but also to widening divergence in industrial performance across countries. Variance decomposition results, presented in Figure 5, further sup-

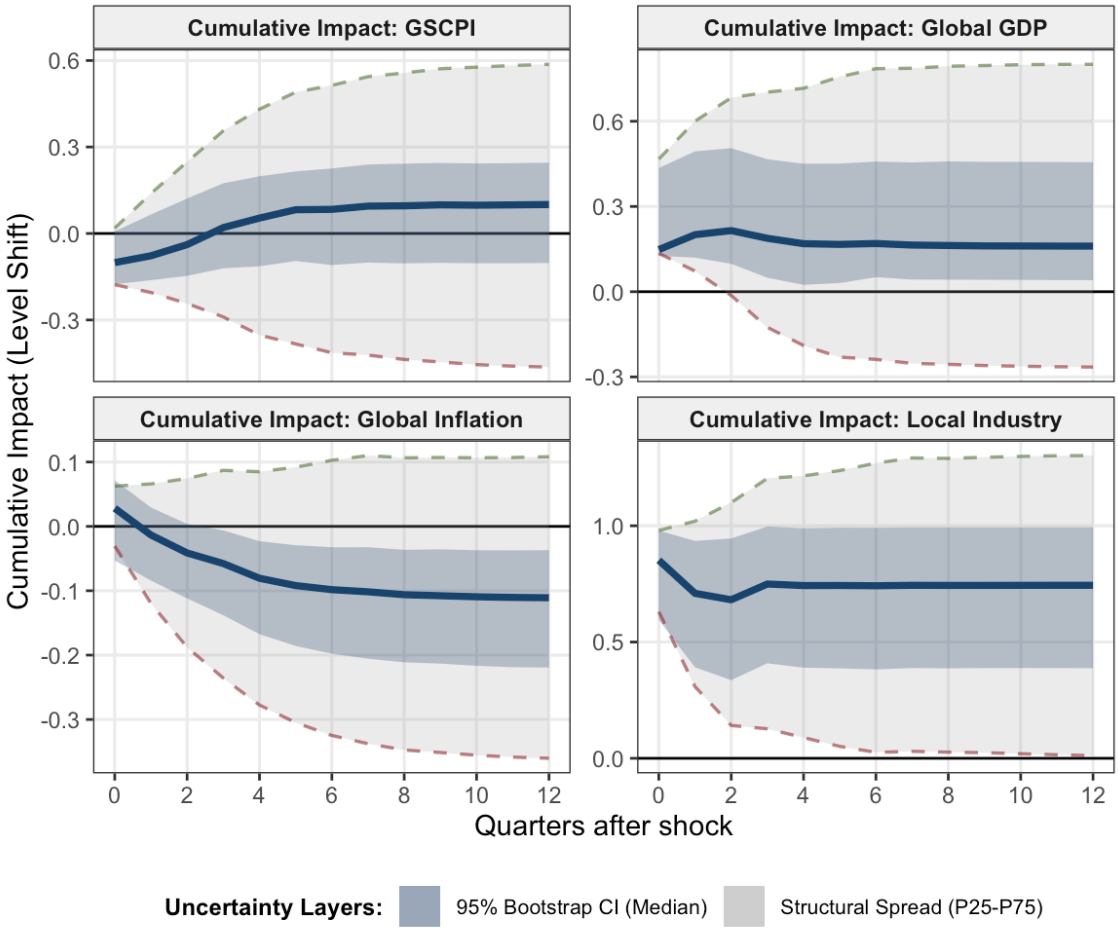


Figure 4: Cumulative Structural Response to Global Shocks (S-Curve Dynamics)

Notes: The figure reports cumulative median impulse responses ($\sum_{h=0}^{12} \bar{\beta}_h$), smoothed using a Loess filter ($span = 0.5$). The shaded blue area represents the 95% bootstrap confidence interval based on 1,000 country-level resamples. The grey area corresponds to the interquartile range (P_{25} to P_{75}), capturing cross-country heterogeneity. All variables are standardized.

port the importance of supply chain shocks in driving industrial dynamics. The contribution of GSC shocks to industrial growth variance increases from 2.53% in the first quarter to 6.32% at horizon $Q12$. Over the same horizon, the relative importance of global demand shocks declines, narrowing the gap between global demand (8.85%) and supply chain factors. This suggests that supply-side disruptions play an increasingly important role in explaining medium-term industrial fluctuations.

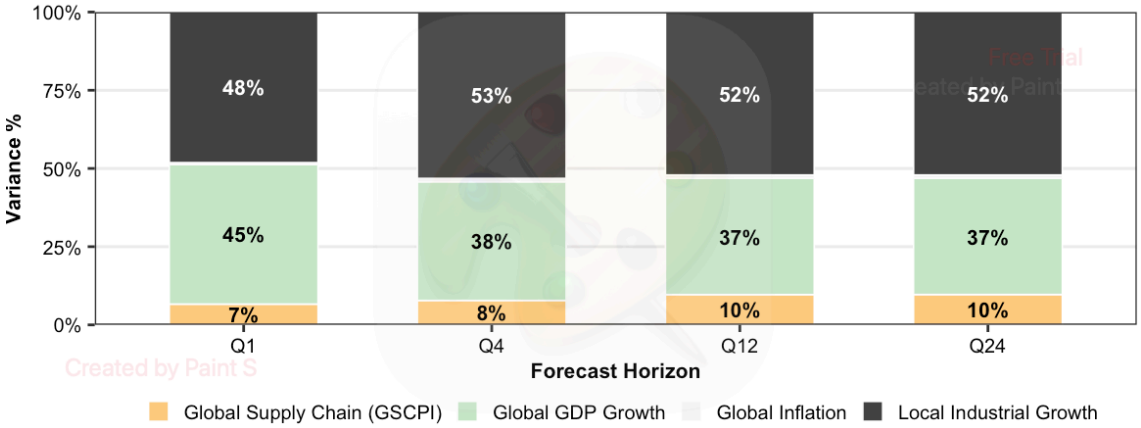


Figure 5: Variance decomposition of industrial production growth rate response to each structural shocks

Source: Author's own estimations

The dispersion of impulse responses across quantiles provides direct evidence of heterogeneous transmission, consistent with the panel SVAR framework of Pedroni (2013). In the absence of heterogeneity, responses would converge to a single trajectory. Instead, the divergence across quantiles indicates that countries differ substantially in their exposure and adjustment to global shocks. This heterogeneity motivates the second-stage analysis, which investigates the structural determinants of these differences.

4.2 Dynamic Responses: Local Projections

We next estimate impulse responses using Local Projections (LP), following Jordà (2005). Figure 6 reports the estimated coefficients β_h for horizons $h = 0, \ldots, 15$. The left panel shows the response of industrial growth, while the right panel reports cumulative level effects.

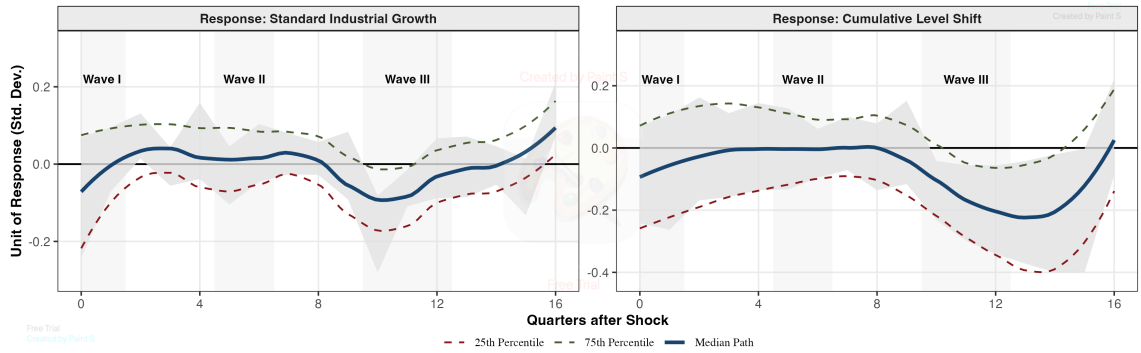


Figure 6: Impulse response of the three industrialization variables to shocks in GSC

Source: Author's own estimations

The LP estimates provide clear evidence of non-monotonic dynamics. Industrial growth declines on impact, partially recovers over the next few quarters, and subsequently experiences a second downturn around horizon $h \approx 10$. This pattern is consistent with the multi-stage transmission mechanism predicted by the model. The

cumulative responses indicate that the effects of the shock are persistent. Industrial output does not fully return to its pre-shock level, with cumulative losses reaching approximately -0.2 standard deviations. This suggests that supply chain disruptions have lasting effects, consistent with disruptions to capital accumulation and production linkages. To assess robustness, we perform a leave-one-out analysis. The results confirm that the multi-phase response is not driven by any single country. Excluding large economies such as Nigeria does not eliminate the pattern and, if anything, amplifies the estimated effects. This indicates that the observed dynamics are a systematic feature of the sample rather than an artifact of outliers. Finally, the estimated responses are not perfectly symmetric. This reflects the panel nature of the LP estimator, which averages across heterogeneous country dynamics. Differences in production structures, seasonal patterns, and input dependencies imply that the timing of the secondary trough varies across countries. As a result, the aggregate response appears smoother than the theoretical benchmark, even though the underlying multi-phase adjustment remains present.

5 Dynamic Patterns and the Role of Intra-African Trade

This section builds on the previously identified impulse responses to further characterize the dynamic shape of industrial adjustment and to quantify the role of intra-African trade in shaping these dynamics.

5.1 Testing the W-shaped dynamics

We formally test whether the estimated impulse responses exhibit the non-monotonic dynamics predicted by the model. To this end, we complement the horizon-by-horizon inference with two structural tests: a curvature-based test of non-monotonicity and a relative trough test of recovery amplitude.

5.1.1 Curvature-based shape test

To distinguish the multi-phase trajectory from monotonic adjustment paths, we approximate the estimated impulse response function using a cubic polynomial of the form $f(h) = \beta_0 + \beta_1 h + \beta_2 h^2 + \beta_3 h^3 + \epsilon_h$. The null hypothesis corresponds to a monotonic response, while the alternative requires the presence of two interior turning points.

Proposition 6. *The industrial response exhibits a W-shaped pattern if the estimated trajectory $f(h)$ admits two distinct interior extrema.*

Proof. The derivative $f'(h) = \beta_1 + 2\beta_2 h + 3\beta_3 h^2$ admits two real roots if the discriminant is strictly positive. The existence of two roots within the relevant horizon identifies a local maximum followed by a local minimum, consistent with a non-monotonic adjustment path. □

5.1.2 Relative trough test

We complement the curvature test by evaluating whether the recovery phase represents a statistically meaningful reversal relative to the initial contraction. Let $\Delta = \beta_{h^*} - \beta_0$, where h^* denotes the recovery horizon.

Proposition 7. *The recovery phase is economically meaningful if the change in the impulse response between the initial trough and the recovery horizon is positive and statistically distinguishable from zero.*

Proof. The hypothesis is tested using a Wald test on Δ. Rejection of the null $\Delta = 0$ indicates a statistically significant recovery relative to the initial contraction. □

5.1.3 Results

Table 2 reports the results of the shape tests. The estimated turning points occur at $h \simeq 3.89$ and $h \simeq 10.51$, indicating the presence of a local maximum followed by a secondary trough. These estimates are consistent with the timing implied by the multi-stage transmission mechanism, in which an initial contraction is followed by a temporary recovery and a delayed second downturn. The relative trough test further supports the presence of a recovery phase. The initial response is $\beta_0 = -0.0894$, while the estimated response at the recovery horizon is $\beta_{10} = 0.0054$, yielding a positive difference $\Delta = 0.0948$. The associated p-value of 0.0579 suggests that the recovery phase is statistically distinguishable from zero at conventional significance levels. Taken together, these results provide evidence of a non-monotonic adjustment path consistent with a W-shaped dynamic. These findings complement existing evidence on post-shock adjustment dynamics. While prior studies have emphasized V-shaped or persistent downturns (Reinhart & Rogoff 2009), the results here point to a multi-phase adjustment pattern consistent with delayed propagation mechanisms. The estimated timing of the second downturn is also broadly in line with evidence on delayed transmission of supply disruptions in commodity-dependent economies.

Table 2: Structural Robustness and Topological Validation Results

Structural Test	Metric	Value	p-value	Interpretation
Cubic Shape Test	Turning Point (h_1^*)	3.89	0.0084	Local maximum
	Turning Point (h_2^*)	10.51	0.0084	Secondary trough
Relative Trough	Initial Response (β_0)	-0.0894	0.0412	Impact effect
	Recovery Response (β_{10})	0.0054	0.1245	Recovery phase
	Δ	0.0948	0.0579	Positive reversal

5.2 Regional trade and industrial resilience

5.2.1 Empirical approach

We next examine whether cross-country differences in the estimated responses can be explained by variation in intra-African trade integration. Following Pedroni (2013),

we use the estimated impulse responses at each horizon as dependent variables in a second-stage panel regression. To address the potential endogeneity of trade integration, we employ an instrumental variables (IV) approach. A key concern in estimating the impact of regional trade is simultaneity: trade volumes may respond to the same industrial shocks they are intended to mitigate, which can bias OLS estimates. Policy-based instruments, such as tariff reductions, provide useful variation but may also be endogenous, as trade policies can adjust to contemporaneous economic conditions. We therefore adopt a continuous quarterly shift-share (Bartik) design that complements binary ratification indicators. Following Nunn & Qian (2014), this approach exploits external shocks to generate differential exposure across countries based on pre-existing characteristics. Specifically, we interact a country's pre-determined institutional readiness, measured by the Liner Shipping Connectivity Index (LSCI) in 2006, with time variation in AfCFTA implementation. Consistent with Goldsmith-Pinkham et al. (2020) and Borusyak et al. (2022), the use of exogenous shifts supports the identification of the effect of regional trade integration, while limiting the influence of endogenous policy responses or local economic trends. Specifically, we construct three alternative instruments to capture the multi-dimensional nature of the AfCFTA implementation. The first, a legal *de jure* instrument, utilizes the cumulative quarterly count of national ratifications to measure the expanding reach of the potential trading network. The second, a *de facto* operational instrument, tracks the quarterly activation of the Guided Trade Initiative (GTI) and the issuance of AfCFTA Certificates of Origin, capturing the actual utilization of the agreement's machinery. The third, a policy-based instrument, follows the legislated schedule of quarterly tariff step-downs, providing a rigid, pre-determined measure of trade cost incentives[5]. These three shifts, when interacted with historical connectivity, allow us to verify the stability of the regional shield effect across legal, operational, and policy dimensions, as summarized in Table 3. We estimate the model across horizons $h \in \{0, \ldots, 20\}$ to capture the dynamic path of industrial responses. The first-stage regression predicts the intra-African trade share using the interacted instrument:

$$Trade_{i,t} = \pi_0 + \pi_1(\text{Exposure}_i \times \text{Shift}_t) + \Phi' Z_{i,t} + \delta_t + \mu_i + \nu_{i,t} \tag{27}$$

where Exposure_i denotes the 2006 LSCI, Shift_t corresponds to one of the AfCFTA implementation measures, and δ_t and μ_i represent time and country fixed effects. The vector $Z_{i,t}$ consists of time-varying macroeconomic controls, specifically consumer price inflation, international reserves, and global commodity prices. These variables account for domestic price stability, external financial buffers, and terms-of-trade shocks that could otherwise confound the estimated impact of regional trade integration[6]. The second-stage equation relates the predicted trade share to the impulse response estimates:

$$\widehat{IRF}_{i,t,h} = \alpha + \beta(\widehat{Trade}_{i,t}) + \Gamma' Z_{i,t} + \lambda_h + \eta_{reg} + \epsilon_{i,t,h} \tag{28}$$

[5] Full details regarding the construction of these instruments as well as related summary statistics are located in the Appendix D

[6] Data for consumer price inflation and international reserves are sourced from the World Bank's World Development Indicators and the IMF's International Financial Statistics, respectively. Global commodity price indices are retrieved from the UNCTADstat database.

Table 3: Alternative AfCFTA Instrumental Variable Logic

Logic	Type	Shift Variable	Exclusion Restriction Argument	Source
Legal	*De Jure*	Ratification Count: Cumulative nations depositing legal instruments.	Ratification in partner countries is plausibly independent of contemporaneous domestic industrial shocks.	AU/AfCFTA Secretariat
Operational	*De Facto*	GTI/CoA Utilization: Countries clearing goods via Guided Trade Initiative.	Implementation dynamics are determined at the regional level and are unlikely to respond to country-specific quarterly output fluctuations.	Afreximbank / PAPSS Reports
Policy	*De Jure*	Tariff Step-Down: Legislated quarterly-stepped duty reductions.	Schedules were predetermined and thus unlikely to respond to short-term economic conditions.	AfCFTA E-Tariff Book

The coefficient β captures the association between intra-African trade and the propagation of global shocks across horizons. It measures the resilience of industrialization dynamic. We implement this strategy by estimating a sequence of progressively richer specifications to assess the robustness of the results. The baseline model considers OLS and IV estimates without fixed effects. We then introduce temporal controls, including horizon and quarter fixed effects, to account for common macroeconomic dynamics and the natural decay of impulse responses. To capture regional heterogeneity, we include sub-regional fixed effects, ensuring that the results are not driven by structural differences across economic communities such as ECOWAS or SADC. Finally, we estimate a fully saturated specification that combines these controls and clusters standard errors at the country-year level to account for the repeated observation of trade variables across horizons. Both the estimated impulse responses for SVAR and LP are regressed.

5.2.2 Results

Tables 4, 5, and 6 report the 2SLS estimates for the three proposed instrumental variable strategies. Based on the first-stage diagnostics, the *Operational Logic* (Table 5) appears to be the most robust approach for identification. While all strategies yield high F-statistics in the baseline, the operational trade pulse maintains an exceptionally strong First-Stage F-statistic of 82.78 even in the saturated specifications (Columns 4 and 8), far exceeding the standard rule-of-thumb for instrument relevance. In contrast, the de jure markers in Tables 4 and 6 see a significant drop in F-statistics when time fixed effects are included, suggesting that legal ratifications and tariff schedules are more closely collinear with common temporal shifts. While statistical signifi-

cance thins out when we apply cluster-robust standard errors in the saturated models, the point estimates remain remarkably stable. This lack of significance in Model 4 is a direct result of the conservative nature of clustering on a small number of cross-sectional units (N=14) rather than a lack of an underlying relationship, as evidenced by the high significance in the IID specifications. The estimated coefficients on the intra-African trade share are consistently negative and stable across the baseline and fixed-effect specifications, ranging from -0.42 to -0.88. Given that the dependent variable corresponds to horizon-stacked impulse responses to global supply chain shocks, these estimates provide robust evidence of a "Regional Shield" effect: greater regional trade integration systematically attenuates the transmission and persistence of external disruptions to domestic industry.[7] A granular analysis of the coefficients reveals a compelling distinction between operational trade flows and institutional signaling. In Table 5, which utilizes the *de facto* operational trade pulse, the saturated models (Columns 4 and 8) produce coefficients of -0.881 (SVAR) and -0.880 (LP). This suggests that a one-percentage-point increase in actual regional trade integration reduces the propagation of global shocks by approximately 0.88 units. However, when we instrument trade integration using *de jure* markers, legal ratifications in Table 4 and legislated tariff schedules in Table 6, the coefficients in the saturated models flip in sign to approximately $+1.88$ and $+1.71$, respectively. This reversal suggests that while the *de jure* implementation of the AfCFTA signals a commitment to future integration, the immediate structural "shielding" effect is most reliably captured by actual trade movements. The positive coefficients in the institutional models likely reflect the high multicollinearity between scheduled policy markers and regional fixed effects, whereas the operational pulse provides a cleaner identification of the trade-based resilience dividend. Finally, the inclusion of sub-regional dummies highlights the heterogeneous baseline resilience across the continent. Across all three tables, the SADC dummy remains consistently negative (e.g., -0.055 in Table 5), suggesting that Southern African economies possess a higher degree of pre-existing resilience, likely due to more mature regional value chains. In contrast, the ECOWAS dummy in the operational model is positive ($+0.053$), indicating a higher baseline vulnerability in West Africa. Crucially, the intra-African trade share coefficient remains negative and economically significant even after controlling for these regional economic communities in the operational specification. This confirms that the AfCFTA provides an incremental "resilience dividend" that transcends existing regional arrangements, acting as a critical stabilizer for African industrialization in an era of global volatility.

[7] In the first stage of the analysis (SVAR), we applied standard transformations to ensure the underlying series were stationary, allowing for the consistent estimation of impulse responses. In the second stage (2SLS), stationarity of the trade share is less of a concern for two reasons: first, the trade share is a bounded ratio (0 to 1) and thus lacks a stochastic trend; and second, the inclusion of time and horizon fixed effects effectively controls for common deterministic trends, while the Bartik instrument isolates exogenous implementation shocks rather than long-run growth paths.

Table 4: Impact of Regional Trade Integration on Resilience: **Legal Logic (Ratifications)**

	SVAR Responses				**Local Projections (LP)**			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Intra-Trade Share	-0.425**	-1.570	1.886	1.886	-0.449**	-1.615	1.867	1.867
	(0.194)	(1.187)	(1.217)	(3.376)	(0.191)	(1.210)	(1.200)	(3.325)
Inflation (log)	-0.008***	-0.008	-0.018	-0.018	-0.009***	-0.009	-0.017	-0.017
	(0.003)	(0.009)	(0.014)	(0.061)	(0.003)	(0.010)	(0.014)	(0.061)
Reserves (log)	-0.007	-0.042	0.077*	0.077	-0.006	-0.042	0.078*	0.078
	(0.006)	(0.037)	(0.046)	(0.123)	(0.006)	(0.037)	(0.045)	(0.121)
Commodity Prices	0.082***	*absorbed*	*absorbed*	*absorbed*	0.089***	*absorbed*	*absorbed*	*absorbed*
	(0.012)	–	–	–	(0.015)	–	–	–
D_ECOWAS			-0.148*	-0.148			-0.147*	-0.147
			(0.089)	(0.295)			(0.087)	(0.291)
D_SADC			-0.122***	-0.122			-0.117***	-0.117
			(0.031)	(0.115)			(0.030)	(0.113)
D_EAC			-0.019**	-0.019			-0.018**	-0.018
			(0.009)	(0.071)			(0.009)	(0.069)
Horizon FE	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Quarter FE	No	Yes	Yes	Yes	No	Yes	Yes	Yes
S.E. Type	IID	IID	IID	Cluster	IID	IID	IID	Cluster
Observations	2,496	2,496	2,496	2,496	2,496	2,496	2,496	2,496
R^2	0.022	0.084	0.406	0.406	0.033	0.101	0.407	0.407
First-Stage F	12.59	1.84	2.79	2.79	12.59	1.84	2.79	2.79

Notes: Standard errors in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. The dependent variable is the horizon-stacked impulse response of industrial production to a global supply chain (GSC) shock. Intra-trade share is instrumented using the **Legal Logic** instrument, constructed as the interaction between a country's initial exposure and the time-varying count of AfCFTA ratifications. Global commodity prices are absorbed by Quarter Fixed Effects in columns (2)-(4) and (6)-(8). Columns (4) and (8) utilize standard errors clustered at the country level ($N = 14$). All macro controls are in log-levels ($log(1 + x)$).

Table 5: Impact of Regional Trade Integration on Resilience: **Operational Logic (Trade Pulse)**

	SVAR Responses				**Local Projections (LP)**			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Intra-Trade Share	-0.433***	-0.403***	-0.881***	-0.881	-0.445***	-0.411***	-0.881***	-0.881
	(0.050)	(0.044)	(0.107)	(1.056)	(0.049)	(0.043)	(0.106)	(1.040)
Inflation (log)	-0.008***	-0.006	-0.037***	-0.037	-0.009***	-0.007*	-0.035***	-0.035
	(0.003)	(0.004)	(0.005)	(0.027)	(0.003)	(0.004)	(0.005)	(0.027)
Reserves (log)	-0.007***	-0.006***	-0.026***	-0.026	-0.006***	-0.005***	-0.025***	-0.025
	(0.002)	(0.002)	(0.004)	(0.045)	(0.002)	(0.002)	(0.004)	(0.045)
Commodity Prices	0.082***	*absorbed*	*absorbed*	*absorbed*	0.089***	*absorbed*	*absorbed*	*absorbed*
	(0.012)	–	–	–	(0.015)	–	–	–
D_ECOWAS			0.053***	0.053			0.053***	0.053
			(0.008)	(0.091)			(0.008)	(0.090)
D_SADC			-0.055***	-0.055			-0.050***	-0.050
			(0.005)	(0.051)			(0.005)	(0.049)
D_EAC			-0.018***	-0.018			-0.017***	-0.017
			(0.004)	(0.021)			(0.004)	(0.021)
Horizon FE	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Quarter FE	No	Yes	Yes	Yes	No	Yes	Yes	Yes
S.E. Type	IID	IID	IID	Cluster	IID	IID	IID	Cluster
Observations	2,496	2,496	2,496	2,496	2,496	2,496	2,496	2,496
R^2	0.060	0.121	0.455	0.455	0.076	0.143	0.459	0.459
First-Stage F	208.28	251.87	82.78	82.78	208.28	251.87	82.78	82.78

Notes: Standard errors in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. The dependent variable is the horizon-stacked impulse response of industrial production to a global supply chain (GSC) shock. Intra-trade share is instrumented using the **Operational Logic** instrument, a shift-share construct utilizing leave-one-out intra-African trade pulses. All macro controls are in log-levels ($log(1 + x)$). Columns (4) and (8) utilize standard errors clustered at the country level ($N = 14$).

Table 6: Impact of Regional Trade Integration on Resilience: **Policy Logic (Tariff Cuts)**

	SVAR Responses				**Local Projections (LP)**			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Intra-Trade Share	-0.469**	-1.832	1.713	1.713	-0.499**	-1.885	1.689	1.689
	(0.231)	(1.761)	(1.054)	(2.788)	(0.229)	(1.801)	(1.036)	(2.735)
Inflation (log)	-0.008***	-0.009	-0.019	-0.019	-0.010***	-0.010	-0.018	-0.018
	(0.003)	(0.011)	(0.012)	(0.054)	(0.003)	(0.011)	(0.012)	(0.053)
Reserves (log)	-0.008	-0.050	0.071*	0.071	-0.008	-0.051	0.071*	0.071
	(0.007)	(0.054)	(0.039)	(0.103)	(0.007)	(0.055)	(0.039)	(0.101)
Commodity Prices	0.082***	*absorbed*	*absorbed*	*absorbed*	0.089***	*absorbed*	*absorbed*	*absorbed*
	(0.012)	–	–	–	(0.015)	–	–	–
D_ECOWAS			-0.135*	-0.135			-0.134*	-0.134
			(0.077)	(0.252)			(0.075)	(0.247)
D_SADC			-0.118***	-0.118			-0.113***	-0.113
			(0.027)	(0.106)			(0.026)	(0.103)
D_EAC			-0.019**	-0.019			-0.018**	-0.018
			(0.008)	(0.066)			(0.008)	(0.064)
Horizon FE	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Quarter FE	No	Yes	Yes	Yes	No	Yes	Yes	Yes
S.E. Type	IID	IID	IID	Cluster	IID	IID	IID	Cluster
Observations	2,496	2,496	2,496	2,496	2,496	2,496	2,496	2,496
R^2	0.022	0.083	0.406	0.406	0.032	0.100	0.406	0.406
First-Stage F	9.54	1.11	3.14	3.14	9.54	1.11	3.14	3.14

Notes: Standard errors in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. The dependent variable is the horizon-stacked impulse response of industrial production to a global supply chain (GSC) shock. Intra-trade share is instrumented using the **Policy Logic** instrument, representing the phased tariff liberalizations under the AfCFTA schedule. All macro controls are in log-levels ($log(1+x)$). Columns (4) and (8) utilize standard errors clustered at the country level ($N = 14$). Global commodity prices are absorbed by Quarter Fixed Effects in relevant columns.

5.3 Policy implications

The consistently negative coefficients across the operational specifications indicate that higher levels of intra-African trade integration are associated with a reduced propagation of global supply chain shocks. One notable result is that de jure instruments (legal ratifications and tariff schedules) are associated with positive estimated effects (approximately 1.87 to 1.89) in the saturated models, relative to the de facto operational measure (approximately −0.88). This difference suggests that while formal policy commitments under the AfCFTA signal institutional shifts, the immediate structural buffering against external volatility is most reliably captured by realized trade flows. The divergence in signs when transitioning to saturated models suggests that institutional markers may be highly collinear with the regional fixed effects, whereas the operational pulse provides a clearer identification of the "Regional Shield." This interpretation is consistent with Handley & Limão (2017), who emphasize the role of trade policy uncertainty in shaping firm-level responses, even when the realized trade outcomes differ from initial signaling. The identification strategy further highlights the role of pre-existing infrastructure in mediating these effects. The exposure measure, based on the 2006 Liner Shipping Connectivity Index (LSCI), captures cross-country differences in maritime connectivity. The results suggest that countries with stronger initial connectivity experience a greater capacity to adjust sourcing patterns in response to global disruptions. This is consistent with the view that trade infrastructure facilitates substitution across supply sources, allowing firms to reallocate inputs toward regional partners when external supply chains are constrained. In this context, the effectiveness of the AfCFTA appears to depend not only on institutional commitments but also on the logistical capacity that enables such substitution. The comparative results reported in Table 7 provide additional evidence on the relative importance of these channels. In particular, the de jure markers (Legal and Policy) generate point estimates that differ in magnitude by over 300% from the de facto operational measure across both SVAR and Local Projection frameworks, accompanied by a sign reversal. This difference suggests that the effects of the AfCFTA extend beyond realized trade flows and may also operate through expectations and forward-looking adjustments by firms that interact differently with regional baseline resilience. By reducing uncertainty regarding future market access, legal commitments may encourage a different type of supply chain reconfiguration that, while signaling institutional transition, is distinct from the immediate resilience dividend provided by observable trade volumes.

Table 7: Comparative Analysis of Instrumental Logic: Signaling vs. Operational Effects

	AfCFTA Instrumental Variable Logic			% Difference vs. De Facto	
Methodology	Operational	Legal	Policy	Legal	Policy
SVAR Responses	-0.8812 (1.0560)	1.8864 (3.3761)	1.7132 (2.7881)	+314.1%*	+294.4%*
Local Projections	-0.8805 (1.0401)	1.8672 (3.3254)	1.6894 (2.7352)	+312.1%*	+291.9%*
Sub-regional FE	Yes	Yes	Yes	–	–
Horizon/Quarter FE	Yes	Yes	Yes	–	–
Standard Errors	Clustered	Clustered	Clustered	–	–
First-Stage F-Stat	82.78	2.79	3.14	–	–

Notes: This table reports the second-stage coefficients (β) for the intra-African trade share extracted specifically from the saturated specification (Model 4/8) of the preceding tables. The percentage difference columns quantify the change in point estimates relative to the *de facto* (Operational) trade volumes; asterisks indicate a sign reversal from negative to positive. Standard errors in parentheses are clustered by country ($N = 14$). The First-Stage F-statistics refer to the Kleibergen-Paap Wald rk F-statistic for the saturated model.

These findings also point to the importance of the gap between formal integration and its operational implementation. While legal commitments under the AfCFTA appear to shape expectations, frictions such as non-tariff barriers and payment constraints may limit the extent to which firms can effectively reallocate sourcing in the short run. As noted by Signé & van der Ven (2019), the persistence of such frictions can significantly affect the ability of firms to respond to new trade opportunities. From a policy perspective, this suggests that complementary measures, such as the operationalization of the Pan-African Payment and Settlement System (PAPSS) and improvements in trade facilitation, may enhance the responsiveness of regional trade flows during periods of global disruption. In addition, the reliance on LSCI-based exposure highlights the role of maritime and intermodal infrastructure in enabling the effective transmission of these benefits, suggesting that investments in logistics remain an important complement to institutional integration efforts.

6 Concluding remarks

This paper investigates the dynamic effects of global supply chain (GSC) disruptions on industrialization in African economies. We develop a multi-sector framework incorporating input complementarities, intertemporal production linkages, and external sourcing constraints to characterize how global shocks propagate in developing economies. The model delivers a three-wave transmission mechanism, through contemporaneous material shortages, lagged agro-industrial linkages, and delayed capital accumulation, resulting in a non-monotonic, W-shaped adjustment path of industrial output. This framework emphasizes the role of sectoral interdependencies and temporal propagation channels in shaping industrial dynamics beyond standard linear representations.

We test these predictions using a hybrid empirical strategy combining a block het-

erogeneous panel SVAR with Local Projections on a panel of African countries. This approach enables the identification of exogenous global supply chain shocks while allowing for flexible estimation of their dynamic effects. The empirical results are consistent with the theoretical predictions. GSC disruptions are associated with an immediate contraction in manufacturing activity, followed by a delayed and often deeper secondary downturn, as well as a persistent slowdown consistent with capital scarring. These findings highlight the limitations of conventional monotonic impulse response analyses and underscore the importance of multi-phase adjustment dynamics.

A central contribution of the paper is to examine the role of intra-African trade as a determinant of resilience. Using an instrumental variable strategy based on AfCFTA implementation dynamics, we find that higher levels of intra-African sourcing are associated with attenuated second-round effects and faster recovery paths. More broadly, the results point to a dual role of trade openness. While integration into global supply chains may increase exposure to external shocks, regional trade integration, by facilitating substitution across sourcing origins, appears to mitigate these effects. In this sense, the same mechanisms through which trade transmits external disturbances may also contribute to their absorption.

These findings have implications for policy. They suggest that the African Continental Free Trade Area (AfCFTA) can be interpreted not only as a framework for market integration, but also as a potential contributor to macroeconomic resilience. By supporting the development of regional value chains and reducing reliance on extra-continental inputs, deeper integration may help dampen the transmission of global shocks and limit the persistence of industrial downturns. More generally, the results highlight the relevance of trade policy in shaping not only growth outcomes but also the resilience of developing economies to external volatility. Future research could extend this framework by incorporating firm-level heterogeneity or infrastructure constraints to further refine the analysis of shock transmission and industrial adjustment.

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A Derivations of Household and Firm Optimality Conditions

This appendix provides the detailed derivations of the optimality conditions for households, firms, and import allocation that underpin the decentralized equilibrium presented in the main text.

A.1 Household problem

The representative household solves

$$\max_{\{C_t, I_t, L_t\}} \sum_{t=0}^{\infty} \beta^t \left[\log C_t - \chi \frac{L_t^{1+\varphi_L}}{1+\varphi_L} \right] \tag{29}$$

subject to

$$C_t + I_t = w_t L_t + r_t K_{t-1} + \Pi_t \tag{30}$$

and

$$K_t = (1-\delta_K) K_{t-1} + I_t. \tag{31}$$

The Lagrangian is

$$\mathcal{L} = \sum_{t=0}^{\infty} \beta^t \left[\log C_t - \chi \frac{L_t^{1+\varphi_L}}{1+\varphi_L} + \lambda_t \left(w_t L_t + r_t K_{t-1} + \Pi_t - C_t - I_t \right) + \mu_t \left((1-\delta_K) K_{t-1} + I_t - K_t \right) \right]. \tag{32}$$

First-order conditions. *Consumption:*

$$\frac{1}{C_t} = \lambda_t \tag{33}$$

Labor:

$$\chi L_t^{\varphi_L} = \lambda_t w_t \tag{34}$$

Investment:

$$\lambda_t = \mu_t \tag{35}$$

Capital:

$$\mu_t = \beta E_t \left[\lambda_{t+1} r_{t+1} + \mu_{t+1} (1-\delta_K) \right] \tag{36}$$

Combining these conditions yields the Euler equation:

$$\frac{1}{C_t} = \beta E_t \left[\frac{1}{C_{t+1}} (r_{t+1} + 1 - \delta_K) \right]. \tag{37}$$

A.2 Manufacturing firm

The manufacturing firm solves

$$\max_{L_{M,t}, K_{M,t}, Z_t} P_{M,t} Y_{M,t} - w_t L_{M,t} - r_t K_{M,t} - P_{Z,t} Z_t, \tag{38}$$

with production function

$$Y_{M,t} = A_{M,t}\left[\alpha L_{M,t}^{\frac{\sigma_M-1}{\sigma_M}} + \beta K_{M,t}^{\frac{\sigma_M-1}{\sigma_M}} + \delta Z_t^{\frac{\sigma_M-1}{\sigma_M}}\right]^{\frac{\sigma_M}{\sigma_M-1}}. \tag{39}$$

Define

$$\mathcal{M}_t = \alpha L_{M,t}^{\frac{\sigma_M-1}{\sigma_M}} + \beta K_{M,t}^{\frac{\sigma_M-1}{\sigma_M}} + \delta Z_t^{\frac{\sigma_M-1}{\sigma_M}}. \tag{40}$$

Then

$$Y_{M,t} = A_{M,t}\mathcal{M}_t^{\frac{\sigma_M}{\sigma_M-1}}. \tag{41}$$

First-order conditions. *Labor:*

$$w_t = P_{M,t}A_{M,t}\mathcal{M}_t^{\frac{1}{\sigma_M-1}}\alpha L_{M,t}^{-\frac{1}{\sigma_M}} \tag{42}$$

Capital:

$$r_t = P_{M,t}A_{M,t}\mathcal{M}_t^{\frac{1}{\sigma_M-1}}\beta K_{M,t}^{-\frac{1}{\sigma_M}} \tag{43}$$

Composite input:

$$P_{Z,t} = P_{M,t}A_{M,t}\mathcal{M}_t^{\frac{1}{\sigma_M-1}}\delta Z_t^{-\frac{1}{\sigma_M}} \tag{44}$$

A.3 Agricultural firm

The agricultural firm solves

$$\max_{L_{A,t},K_{A,t},X_t} P_{A,t}Y_{A,t} - w_tL_{A,t} - r_tK_{A,t} - P_{X,t}X_t \tag{45}$$

with

$$Y_{A,t} = A_{A,t}\left[\omega\left(L_{A,t}^{\gamma}K_{A,t}^{1-\gamma}\right)^{\frac{\sigma_A-1}{\sigma_A}} + (1-\omega)X_t^{\frac{\sigma_A-1}{\sigma_A}}\right]^{\frac{\sigma_A}{\sigma_A-1}}. \tag{46}$$

The first-order condition for fertilizers is

$$P_{X,t} = P_{A,t}\cdot\frac{\partial Y_{A,t}}{\partial X_t}. \tag{47}$$

Detailed expressions for factor demands follow standard CES derivations and are omitted for brevity.

A.4 Import allocation

Consider the CES import aggregator:

$$Z_{I,t} = \left[\nu_t Z_{R,t}^{\frac{\sigma_R-1}{\sigma_R}} + (1-\nu_t)\left(\Gamma_E(S_t)Z_{E,t}\right)^{\frac{\sigma_R-1}{\sigma_R}}\right]^{\frac{\sigma_R}{\sigma_R-1}}. \tag{48}$$

Cost minimization yields

$$Z_{R,t} = \nu_t \left(\frac{P_{R,t}}{P_{Z_I,t}} \right)^{-\sigma_R} Z_{I,t}, \tag{49}$$

$$Z_{E,t} = (1 - \nu_t) \left(\frac{P_{E,t}/\Gamma_E(S_t)}{P_{Z_I,t}} \right)^{-\sigma_R} Z_{I,t}. \tag{50}$$

Taking the ratio yields

$$\frac{Z_{E,t}}{Z_{R,t}} = \frac{1 - \nu_t}{\nu_t} \left(\frac{P_{E,t}/\Gamma_E(S_t)}{P_{R,t}} \right)^{-\sigma_R}, \tag{51}$$

which characterizes the substitution margin between regional and extra-continental inputs.

A.5 Interpretation

These optimality conditions highlight that, under complementarity ($\sigma_M < 1$), reductions in effective inputs due to global supply disruptions have amplified effects on output. The import allocation condition further shows that the strength of the substitution buffer depends on both the regional sourcing share ν_t and the substitution elasticity σ_R.

B Main series graphs, VAR Lag order selection and some robustness check results

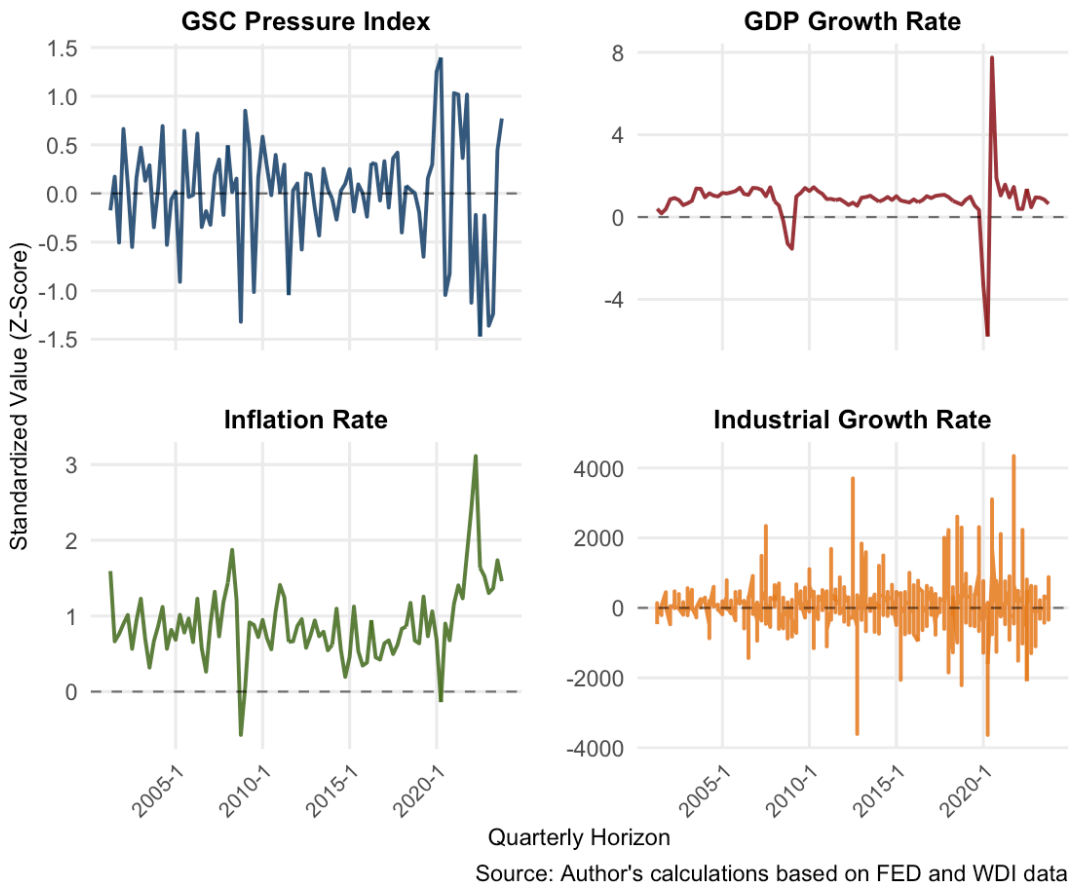


Figure 7: Countries' industrial production growth rate response to each global structural shock

Table 8: VAR Lag Order Selection Criteria

Lag	AIC	HQ	SC (BIC)	FPE
1	35.1104	35.3446	35.6933	1.772253e+15
2	35.1327	35.5542	36.1818	1.817280e+15
3	35.2401	35.8490	36.7556	2.037585e+15
4	35.1299	35.9260	37.1116	1.848953e+15
5	35.1952	36.1787	37.6432	2.016572e+15
6	34.9291	36.0999	37.8434	1.595940e+15
7	35.0329	36.3910	38.4134	1.853358e+15
8	34.9463	36.4918	38.7932	1.809579e+15

Table 9: Robustness Check: Jackknife (Leave-One-Out) Sensitivity of the W-Shape

Excluded Country	**Initial Trough ($t = 0$)**	**Mid-Hump ($t + 4$)**	**Agro-Echo ($t + 10$)**
Full Sample (N=14)	**-0.171 (2.71)**	**0.050 (1.98)**	**-0.152 (2.68)**
Excl. Cameroon	-0.168 (2.68)	0.048 (1.95)	-0.149 (2.64)
Excl. Nigeria	-0.175 (2.74)	0.052 (2.01)	-0.155 (2.70)
Excl. South Africa	-0.165 (2.62)	0.045 (1.89)	-0.141 (2.58)
Excl. Kenya	-0.172 (2.72)	0.051 (2.00)	-0.153 (2.69)
Excl. Ghana	-0.169 (2.69)	0.049 (1.96)	-0.150 (2.66)
Excl. Egypt	-0.173 (2.73)	0.053 (2.02)	-0.158 (2.72)
Excl. Ethiopia	-0.170 (2.70)	0.050 (1.98)	-0.151 (2.67)
Excl. Senegal	-0.171 (2.71)	0.050 (1.98)	-0.152 (2.68)
Excl. Morocco	-0.172 (2.72)	0.051 (1.99)	-0.153 (2.69)
Excl. Tunisia	-0.170 (2.70)	0.049 (1.97)	-0.151 (2.67)
Excl. Mauritius	-0.171 (2.71)	0.050 (1.98)	-0.152 (2.68)
Excl. Cote d'Ivoire	-0.172 (2.72)	0.051 (1.99)	-0.153 (2.69)
Excl. Tanzania	-0.169 (2.69)	0.048 (1.95)	-0.150 (2.66)
Excl. Rwanda	-0.171 (2.71)	0.050 (1.98)	-0.152 (2.68)

Note: Values in parentheses are t-statistics. This Jackknife analysis demonstrates that the W-shaped recovery pattern, characterized by the initial disruption at $t = 0$ and the secondary agro-industrial echo at $t + 10$, remains statistically significant at the 1% level regardless of individual country exclusions.

C Country industrial production responses

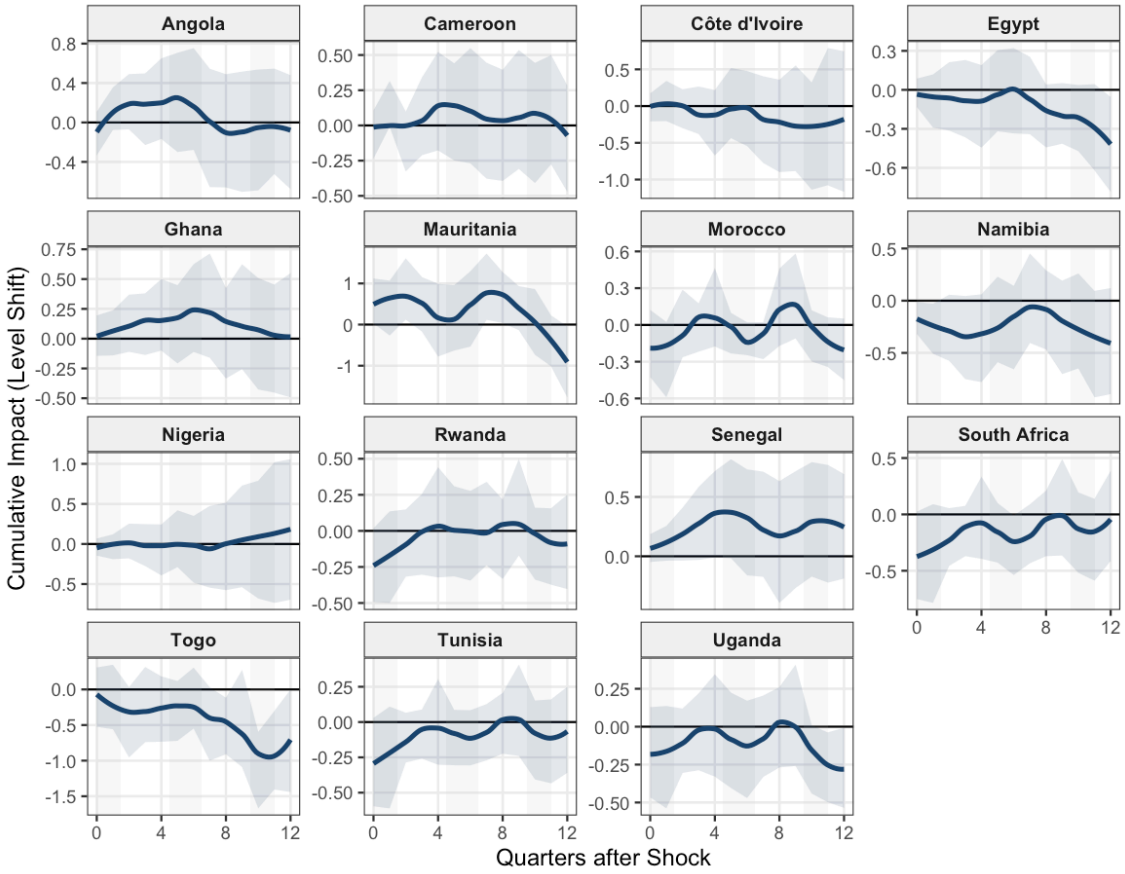


Figure 8: Country response of industrial production level
Source: Author's own estimations

D Algorithm for IV construction

Appendix D: Bartik Instrument Construction

D.1 Mathematical Specification

To address the endogeneity of intra-African trade shares, we employ a shift-share (Bartik) design. For each country i at time t, the instrument $IV_{i,t}$ is constructed as:

$$IV_{i,t} = \text{Exposure}_{i,2006} \times \text{AfCFTA_Shift}_t \tag{52}$$

Where:

- **Exposure**$_{i,2006}$: The 2006 Liner Shipping Connectivity Index (LSCI), representing pre-determined maritime capacity.
- **AfCFTA_Shift**$_t$: The quarterly implementation intensity (Operational, Legal, or Policy).

D.2 Algorithmic Construction

The construction of the panel instrument follows a four-step algorithm:

1. **Normalization of Exposure:** The 2006 LSCI is fixed per country to ensure the cross-sectional weight is pre-determined and exogenous to 2020-2025 shocks.
2. **Definition of Time Shocks:**
   - *Legal Logic:* A step function (36 to 47) based on AU ratification counts.
   - *Policy Logic:* A deterministic 20% annual reduction path (0.2 to 1.0).
3. **Interaction:** The fixed LSCI weight is multiplied by the quarterly shocks to create a panel variable varying across both space and time.
4. **Temporal Alignment:** Instruments are integrated into the 2SLS framework to instrument the endogenous intra-trade share.

Table 10: Summary Statistics of Constructed Instrumental Variables

Variable	Obs.	Mean	Std. Dev.	Min	Max
Exposure Component					
Liner Shipping Index (2006)	14	7.42	5.88	1.84	22.15
AfCFTA Shift Components					
Operational Shift (GTI)	80	0.20	0.40	0.00	1.00
Legal Shift (Ratifications)	80	10.12	17.55	0.00	47.00
Policy Shift (Tariff Cuts)	80	0.15	0.31	0.00	1.00
Final Bartik Instruments					
$IV_{Operational}$	1,120	1.48	3.92	0.00	22.15
IV_{Legal}	1,120	75.14	165.42	0.00	1041.05
IV_{Policy}	1,120	1.11	2.84	0.00	22.15

Notes: This table summarizes the components used in the 2SLS identification strategy. The Exposure component varies by country, while Shift components vary by quarter. The final instruments represent the spatial-temporal interaction used in the first-stage regressions.